The Socioeconomic and Environmental Impacts of the Climate Policies in China

——Based on the CGE Analysis

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PhD Degree Thesis

Abstract

This thesis is intended to analyse the policy effects of the simulated Chinese climate policies. Without considering any benefits and influential factors, the carbon tax could effectively reduce the carbon emissions at the price of the welfare loss. Considering its ancillary (health) benefit, the tax will induce less emission reduction and welfare loss. The primary (climate) benefit of the tax will increase the carbon emissions, decrease the carbon intensity, and induce an economic boom. The induced technological change (ITC) of the carbon tax will have negative impacts on the carbon emissions, and it will increase the real GDP (RGDP) but decrease the household welfare. The inequality impacts of the carbon tax depend on the distribution of the climate damages and the payments of the abatement costs. Recycling the tax revenues will also affect the inequality impacts of the tax. Under the impacts of the projected urbanisation, the carbon tax will induce more emission reduction, less RGDP loss, and more household welfare loss. With the same amount of the targeted emission reduction as the carbon tax, the emission trading scheme (ETS) policy will induce the higher household welfare compared to the carbon tax.

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Statement of Originality

This thesis is originally written on my own and all else is clearly referenced.

Copyright Declaration

Chapter 0: Overview

Background

Human activity is the dominant cause of the observed global warming since the mid-20th century (IPCC 2013). Having witnessed rapid economic growth for more than thirty years, China has become the leading carbon emitter with its carbon emissions exceeding the sum of the EU and US emissions since 2013, according to the World Bank (WB) data. Facing increasing pressure from the global community to abate carbon emissions in the context of international climate change agreements, the Chinese government has implemented climate policies to mitigate the anthropogenic emissions.

As a kind of governmental interventions on the market mechanism, a climate policy tends to result in deadweight loss of social welfare as the market becomes imperfectly competitive. A growing literature attempts to assess the impacts of climate policies on the Chinese economy, aiming to assess the optimal policies maximising benefits or minimising costs (Chi, Guo et al. 2014, Liu and Lu 2015, Sun and Kuang 2015, Li and Jia 2017, Li, Dai et al. 2018). However, the aforementioned work largely overlooked positive side-effects of climate policies. This is because the benefits of climate policies are hard to quantify. For example, because carbon emissions and air pollutant emissions often originate from the same stationary and mobile sources (Workman, Blashki et al. 2019), a climate policy which curbs carbon emissions is likely to reduce air pollutant emissions. However, this benefit of a climate policy is usually neglected in the literature.

Overlooking the benefits of a climate policy is likely to reduce the governmental willingness of policy implementation. Conversely, accounting for the benefits increases the attractiveness of a climate policy, and this evidence can be found globally. For example, Buonocore, Lambert et al. (2016) examined the costs and health co-benefits for a policy resembling the US Clean Power Plan, empirically showing that the simulated climate policy led to the monetised value of the health co-benefits exceeding costs in 10 of 14 power regions. Hence, it is important that the benefits of a climate policy should be unbiasedly modelled.

The induced technical change, income distributional impacts, and the urbanisation may also influence the effects of a climate policy on the emissions and welfare. However, these influential factors are usually overlooked in the literature. Consequently, a biased evaluation may provide misleading policy recommendations. In this thesis, I attempt to quantify the benefits and influential factors of the carbon tax in comparison with the Emission Trading Scheme (ETS) to determine which climate policy is preferable in China. I hope the unbiased policy evaluation could have practical meanings for the government.

Policy Background

On June 30th, 2015, China submitted its Intended Nationally Determined Contributions (INDC) to the United Nations Framework Convention on Climate Change (UNFCCC). The INDC requires China to peak its emissions around 2030 and make the best efforts to peak early; lower its emissions per unit of GDP by 60% to 65% from the 2005 level (NDRC 2015). To achieve these mitigation targets, the Chinese government has to implement climate policies to curb its increasing emissions. If the current existing policies remain unchanged, the target to peak the emissions in 2030 is very challenging as the promoting effects of the GDP growth on the emissions are much larger than the inhibiting effects of the technological advancement (Li and Qin 2019). Therefore, the Chinese government should take more measures to reduce its emissions.

A mitigation target directly determines the amounts of emission reduction that a climate policy should achieve. For example, as the mitigation target becomes more ambitious, more climate policies need to be implemented or the existing policies need to be strengthened (Guo and Liu 2016). Previously, carbon taxes and emission trading schemes (ETS) are the two most popular climate policies to realise a mitigation target (Li and Jia 2016, Li and Jia 2017, Bi, Xiao et al. 2019). The fundamental principle underlying a carbon tax and ETS policy is the same: a price is set for emitting greenhouse gases, either through a specific tax or the requirement to acquire a permit (Allan, Lecca et al. 2014). In other words, a carbon tax attempts to regulate the economy by the optimal carbon price, whereas an ETS policy attempts to regulate the economy by the optimal carbon quotas at the given abatement target. For the simulated carbon tax and ETS policy in this paper, I assume that there are no uncertainties about what interest rate should be used to discount costs and benefits of the climate change, according to Weitzman (2007).

Generally, the implementation of a carbon tax requires the government to play an important role in the economy, while the implementation of an ETS requires a solid carbon market be established (Liu and Lu 2015). Considering the strong government and relatively undeveloped carbon market, a carbon tax is more appealing in China. This is because attempts to implement a pilot ETS in the seven Chinese provinces encountered problems. For example, the large carbon quotas led to a low and unstable carbon price, inducing an inactive and ineffective carbon trading market (Li and Jia 2016). Compared to an ETS, a carbon tax promotes energy-saving technologies and optimises energy consumption structure, but its negative effect on GDP is relatively small (Chi, Guo et al. 2014). Therefore, "a carbon tax is recognised as one of the most cost-effective economic instruments to control carbon emissions", according to Li, Dai et al. (2018) who examined the policy effects of a regional unbalanced carbon tax.

As a kind of governmental interventions on the market mechanism, a carbon tax inevitably results in deadweight loss so that the economy arrives in a new but distorted equilibrium. The carbon tax rate is usually treated as an exogenous variable, shown in Eq. (0.1), where Tax_j is the tax revenues from the consumption of Energy j; EC_{ij} refers to the consumption of Energy j in Sector i; PE_j stands for the price of Energy j; τ_j is the tax rate of Energy j. A subsidy that lowers the energy price can be also incorporated in Eq. (0.1), by specifying $\tau_j < 0$ (Sue Wing 2004). The tax rate can be also introduced as an endogenous variable to internalise the impacts of the climate change and correct the market failure. Hence, an optimal carbon tax may result in superior emission mitigations with minimal negative or even positive socioeconomic impacts (Duan, Zhu et al. 2014). This is the case in Yahoo and Othman (2017) who evaluated the economic impacts of the climate policies in Malaysia, concluding that the negative macroeconomic impacts of the carbon tax would be not very large in Malaysia.

$$Tax_j = \sum_i EC_{ij} * PE_j * \tau_j \tag{0.1}$$

In the literature, a carbon tax, imposed on the consumption of fossil fuels, usually belongs to the domain of Pigouvian taxes. Proposed by Pigou, a Pigouvian tax is a tax imposed on the economic activities to internalise the negative externalities, including air pollution and environmental degradation (Baiardi and Menegatti 2011). There is a negative link between the innovation-inducing and emission-reduction effects of a Pigouvian tax: the smaller is the tax's Pigouvian effect on reducing emissions, the larger is its indirect effect on spurring innovation and diffusing environmentally clean technologies (Hattori 2017). Moreover, a Pigouvian tax overlooks the potential action of an economic agent caused by the incurred private welfare loss. For example, an increase in the energy price owing to a Pigouvian tax causes the production and consumption to shift to a less carbon-intensive equilibrium. Those sectors possessing a high proportion of carbon-intensive assets are likely to experience considerable costs incurred in this shift (Jenkins 2014), and thus they are likely to mount vociferous oppositions to the Pigouvian tax.

A Pigouvian tax is usually viewed as the economically optimal or "first-best" policy to address climate externalities by economists (Jenkins 2014). A first-best climate policy is an ideal climate policy with perfect foresight and full policy implementation (Ebi and Yohe 2013). A first-best policy needs to be implemented in a first-best world without market imperfections, institutional and informational constraints, delayed policy implementation, or social preferences (Ebi and Yohe 2013). In the reality, such ideal climate policies are unrealistic, because the actual world is quite different from the ideal world.

To accommodate the socioeconomic constraints in the real world where the Pareto optimal condition can be hardly attained (Bennear and Stavins 2007, Jenkins 2014), a second-best or mixed climate policy is preferable. A second-best climate policy usually includes the use of multiple policy instruments and can be justified as optimal under a fairly broad set of circumstances in a second-best world (Bennear and Stavins 2007). In other words, a second-best climate policy is suboptimal to address externalities in the presence of one or more binding constraints (Jenkins 2014). Nevertheless, compared to a first-best climate policy, a second-best climate policy has economic inefficiencies (Garnache, Mérel et al. 2017).

Despite the inefficiencies, the merits of a second-best or mixed climate policy have been already proved in the literature. For example, Li and Jia (2017) analysed the economy, energy, and environment impacts of the carbon tax, ETS, and mixed policy in China, concluding that the mixed policy was more effective than a single policy in the reduction of the primary energy consumption. Moreover, Sun and Kuang (2015) investigated the direct and cascaded effects of the hybrid policy in China, arguing that the mixed policy was highly recommended because of its significant lower economic loss, lower energy utilisation costs, and practical robustness against the fluctuation of the energy market and carbon market.

In a mixed climate policy, a carbon tax is usually implemented in combination with other policies to reinforce the emission reduction effect or diminish the social welfare loss of the tax. Recycling the tax revenues is usually implemented as the complementary policy of the tax. Empirical evidence on the merits of the revenue recycling can be found worldwide. For example, Frey (2017) assessed the policy effects of the carbon tax on the Ukrainian economy and environment, arguing that there would have been a net increase of the social welfare if the carbon tax revenues had been recycled through a reduction of the indirect taxes in Ukraine; van Heerden, Blignaut et al. (2016) modelled the possible impacts of the carbon tax on the South African economy, concluding that the negative effect of the carbon tax on the GDP was greatly reduced by the recycling of the tax revenues in South Africa. In the case of China, Zhang, Zhang et al. (2017) recycled the carbon tax revenues to reduce the capital tax or support the clean energy subsidy, concluding that the mixed policy could achieve the target of reducing the emissions more effectively and efficiently than a single carbon tax. Similarly, Xiao, Niu et al. (2015) explored the impacts of the environmental tax on the Chinese economy, empirically showing that the carbon tax refund induced a recovery in the GDP and a promotion in the low-emission industries in China.

Major Indexes Denoting the Socioeconomic Status

The IPAT identity is a widely used term for analysing the effects of human activities on the environment (York, Rosa et al. 2003) where “I” is environmental impacts, “P” stands for population, “A” denotes affluence and “T” is short for technology. The IPAT identity means that environmental impacts are the product of population, affluence, and technology. In this thesis, the environmental impacts mainly refer to the socioeconomic impacts of the anthropogenic emissions. However, as the three influential factors are too summative, each factor needs to be decomposed in order that the whole picture of the economy is captured clearly.

The population factor includes population growth rate, age structure, and urban-rural population ratio. In China, the population growth rate seems to be not a very important factor that drives the carbon emissions, as it will diminish to zero and even negative owing to the low fertility rate below the replacement level for a long time (Zheng 2016). The age structure could have profound socioeconomic impacts owing to the low fertility rate, longer life expectancy, and higher survival rate (Zheng 2016). One widely used measure of ageing is the proportion of aged population (Scherbov and Sanderson 2016). If the proportion of the population aged over 60 or 65 is larger than 10% or 7% respectively, population ageing is considered to occur (Zheng 2016). At present, the rapidly ageing population becomes unaffordable because of the low security and income level with the weak ability to resist risks; the significant growth in demands for care giving but a shortage of care-giving service resources (Jiang, Yang et al. 2016). Although population growth rate and population ageing may not directly affect emissions, these demographic factors could lay socioeconomic impacts, which will affect emissions indirectly.

Another distinguished feature of the Chinese population is the rapid increase of the urban population. In the period 1978–2012, the fraction of the Chinese population dwelling in cities increased from 17.9% to 52.6% (Bai, Shi et al. 2014). Such rapid urbanisation may lay significant impacts on the environment. Urbanisation generally affects carbon emissions in three aspects: residential and industrial energy consumption; energy used by the construction sector; conversion of grasslands and woodlands (Bekhet and Othman 2017). These three aspects imply that urbanisation may positively influence carbon emissions. Conversely, at a higher level, urbanisation may also decrease carbon emissions by reducing road energy use, which was empirically proven in Norway (Liu, Huang et al. 2017a). Hence, an Environment Kuznets Curve (EKC) may exist between urbanisation and carbon emissions (Abdallh and Abugamos 2017).

Affluence is usually measured by GDP, which denotes the level of economic development for a certain region within a given period. The EKC theory indicates that GDP may have an inverted-U relation with carbon emissions. As China is still in the process of industrialisation, economic growth was the dominant factor in increasing the emissions in 1996–2011, according to Xu, Zhao et al. (2014) who decomposed the Chinese sectoral emissions. Considering that China has experienced a slower GDP growth rate in recent years, the GDP may have a lower impact on the carbon emissions in the future. However, Zhou, Wang et al. (2018) explored the socioeconomic determinants of the carbon emissions in China, concluding that the GDP impact on the emissions would become more significant in the future than at present.

Affluence is also influenced by capital accumulation, which may induce technological advancement and thus affect carbon emissions (Liu, Guo et al. 2017). Generally, capital accumulation includes the accumulation of physical and human capital. How physical capital affects emissions is contrary to the way that human capital changes emissions. Because of its significant role in booming economic growth (Du, Wang et al. 2014), an increase in physical capital will lead to further use of energies, which implies that higher physical capital intensity may cause more pollution (Shimamoto 2017). Conversely, an increase of human capital may diminish the use of fossil fuels and thus reduce the anthropogenic carbon emissions (Bano, Zhao et al. 2018). This is because human capital may provide the potential minds to understand the energy security and environmental issues, and the knowledge or skills to develop renewable energy (Bano, Zhao et al. 2018). Overall, physical capital accumulation may positively influence emissions, whilst human capital accumulation may influence emissions in the opposite direction.

Affluence is also affected by air pollution which induces individual disutility. Having experienced the rapid economic growth over the past few decades, China is now facing serious air pollution, which arouses wide concern about the public health owing to the increasing mortality and morbidity. The severe air pollution is also criticised for the induced economic loss in urban areas, according to Zhan, Kwan et al. (2017) who identified the spatiotemporal variations of the air pollution and the associated driving factors of the pollution in China.

Technological advancement is mainly denoted by the decrease of carbon intensity, which is defined as the ratio of CO_2 emissions to the total added values (Liu, Bai et al. 2018). When the GDP growth rate is greater than the increase rate of carbon emissions, the carbon intensity would decrease, according to Ye, Xie et al. (2018) who predicted the carbon intensity in the Pearl River Delta region of China. Although China's carbon intensity has been declining recently (Liu, Bai et al. 2018), it remains to be seen whether the carbon intensity will continue to decline in the future to meet the INDC target of decreasing the carbon intensity in 2030 to 60%–65% of the 2005 level.

Research Questions

This paper aims to evaluate the socioeconomic and environmental effects of the Chinese carbon tax and ETS policy less biasedly, compared to the literature, by considering the influential factors, namely the ancillary benefit, primary benefit, technical impacts, inequality impacts, and urbanisation impacts. For the other factors, like the demographic factors and capital accumulation, are exogenously determined in the policy evaluation framework. In addition, I attempt to compare the policy effects of the carbon tax and ETS policy in this paper.

Specifically, I will answer the following research questions in this paper:

1.Considering all the influential factors, will the designed carbon tax help China meet the INDC target of peaking the emissions and intensity reduction in 2030?

2.At the same abatement target, will the carbon tax or ETS policy induce a higher real GDP (RGDP) and household welfare? Hence, I will answer whether the carbon tax or ETS policy is preferable.

Chapter 1–6 will answer the first research question, whilst Chapter 7 will answer the second research question.

Research Methods

Nowadays, a Computable General Equilibrium (CGE) model (Johansen 1960) has already become a standard and useful tool in the intermediate and advanced macroeconomics for empirical studies. Specifically, policy simulation is widely conducted to evaluate the costs and benefits through analysing aggregate welfare change and distributional impacts prior to the implementation of the envisaged policies. In this thesis, a dynamic recursive CGE model is the basic research framework and used to numerically solve the market clearance after the occurrence of a shock using the given economic data. With the detailed disaggregation of the electricity sector in the CGE model, the carbon tax will not adversely affect the development of the electricity subsectors exploiting renewables only.

As carbon emissions and air pollutant emissions often originate from the same stationary and mobile sources (Workman, Blashki et al. 2019), a climate policy which curbs carbon emissions is likely to reduce air pollutant emissions, too. Because the improved air quality may induce health benefits, climate policies could become more attractive. Unfortunately, researchers tend to overlook such health benefits when evaluating climate policies in the literature. In this thesis, the health benefit of the carbon tax is modelled within the framework of the CGE model. The result comparison between the model considering the health benefit with the one excluding the benefit will reveal to what extent the health benefit increases the attractivity of the carbon tax.

The primary aim of climate policies is to protect the climate (Rubbelke 2006). Unfortunately, as the climate belongs to the domain of public goods, primary benefits of climate policies are usually neglected in the literature, owing to the difficulties in quantification. An integrated assessment model (IAM) that integrates knowledge from two or more domains into a single framework (Nordhaus 2018) is becoming more and more popular in the literature to model climate issues. One of the earliest IAMs to model climate change was the Dynamic Integrated model of Climate and the Economy (DICE) model, dating back to Nordhaus (1992). As "the projections of most environmental variables have seen relatively small revisions" in the family of the DICE models (Nordhaus 2018), a DICE model is employed to quantify primary benefits of the simulated carbon tax.

The United Nation Framework Convention on Climate Change (UNFCCC) has stressed the role of technical progress on the mitigation of the climate change (Akhavan and Jabbari 2007). Hence, the endogenization of technical progress could influence the costs or benefits of a climate policy, which makes the policy implementation less or more appealing. In this thesis, a technical index, which is a formula of energy and nonenergy efficiencies, is defined to show the technical level before and after the carbon tax. This technical index affects both economic growth and anthropogenic emissions.

Unexpectedly, the poor suffered disproportionally from the climate change, according to Althor, Watson et al. (2016) who empirically determined the relationship between countries' greenhouse emissions and their vulnerability to negative impacts of the climate change. Nevertheless, a climate policy could reinforce such inequality, according to Fremstad and Paul (2019) who estimated the household carbon footprints and examined the policy effects of the tax on the multiple forms of the inequality. To model the inequality impact of the carbon tax, I divide the representative household into three subgroups, namely low-income, middle-income, and high-income subgroup. The income and consumption distribution among the subgroups may change if a climate policy is implemented. This is because the income sources and marginal propensity to consume are different among the subgroups. Therefore, the inequality condition is likely to change under the implementation of the carbon tax, and the varied inequality condition may also affect the policy effect of the tax in return.

The socioeconomic impact of the rapid Chinese urbanisation, projected in 2018 World Urbanisation Prospects (WUP) by United Nations (UN), is modelled using an autoregressive distributed lag (ARDL) model, because ARDL models provide reliable results when variables are in mixed order of stationarity (Kalmaz and Kirikkaleli 2019). The results of the ARDL model show the projected percentage impacts of the urbanisation, which are inputted into the CGE framework, and the new model is called the urbanisation model. The result comparison between the urbanisation model, defined in this chapter, with the inequality model, defined in the previous chapter, will answer to what extent the projected urbanisation affects the policy effect of the carbon tax.

Finally, I compare the policy effect of the carbon tax with the Emission Trading Scheme (ETS). This is because an ETS is another very popular climate policy in the literature. The simulated ETS policy is deigned to have the same emission reduction effect as the corresponding tax but different welfare effect to make an easy comparison. The comparison will reveal whether the carbon tax or ETS is preferable. In this chapter, I will consider the influential factors of the ETS policy, including the quantities of the initial quotas, ratio of the free quotas, carbon trading, and trading of the free quotas.

The Tinbergen Rule states that efficient policy requires at least as many independent policy instruments as there are policy targets (Schader, Lampkin et al. 2014). In this paper, the simultaneous consideration of the externalities may induce inefficiencies. To achieve the most efficient policy effects, each externality should be addressed by a unique policy instrument. Hence, a uniform carbon tax or ETS policy, simulated in this paper, may not induce the most efficient policy effects, considering the ancillary and primary benefits and influential factors.

Innovations

I have employed a dynamic recursive CGE model to study the policy effects of the Chinese carbon tax. In the CGE model, the detailed disaggregation of the electricity sector separates the subsectors exploiting fossil fuels from those exploiting renewables. This disaggregation protects the development of renewable energies from the adverse effects of the simulated carbon tax.

I have modelled the ancillary benefit as the improvement in the labour health and thus the increase in the productivity originating from the reduction of the $PM_{2.5}$ concentrations. I have also modelled the primary benefit of the Chinese carbon tax, using the DICE/RICE model. Hence, I have innovatively modelled both the ancillary and primary benefits of the carbon tax within the CGE policy evaluation framework.

I have quantified the induced technological change (ITC) of the carbon tax basing on the technical index, which is a function of the energy-use efficiency (EUE), energy-production efficiency (EPE), and nonenergy-production efficiency (ENE).

I have introduced the inequality impacts into the CGE framework basing on the consumer behaviour study of Johansson-Stenman, Carlsson et al. (2002). The inequality condition is measured by the Palma ratio, and the inequality impacts are measured by the relative utility.

I have used the ARDL model to quantify the urbanisation impacts, which are inputted into the CGE policy evaluation framework. Hence, I have innovatively modelled the urbanisation impacts on the policy effects of the carbon tax.

I have designed the ETS policy under the same abatement target as the carbon tax to compare the welfare effects. In other words, the abatement target of the designed ETS policy is based on the tax rate of the carbon tax. Hence, the comparison of the welfare effects will unbiasedly reveal which climate policy is preferable.

Chapter 1: The CGE Model Structure and Framework

Introduction

The accelerating global climate change needs to be regulated by the government as the market price of carbon emission fails to internalise the climate damages (Jorgenson, Goettle et al. 2009). Consequently, the market mechanism cannot allocate resources efficiently and effectively as the climate belongs to the domain of public goods. The nonexcludable and nonrivalry features of the climate justify public initiatives to intervene the anthropogenic emissions. Such intervention is necessary to overcome the shortcomings of the market mechanism in the climate issues; otherwise, a rational economic entity will exploit the climate as much as possible. With climate regulations, the social costs of carbon (SCC) are internalised as a part of production costs (Zhen, Tian et al. 2018). The internalisation of the SCC will induce a new equilibrium where the benefits of an entity equal its individual costs plus social costs. The role of climate policies to arrive at socioeconomically efficient conditions is becoming more and more important facing the accelerating global warming (Ding, Maibach et al. 2011, McCright, Dunlap et al. 2013).

Within the domain of climate policies, a carbon tax is recognised as one of the most cost-effective economic instruments to abate anthropogenic emissions (Li, Dai et al. 2018). This is because a carbon tax is beneficial to energy-saving, emission-reduction, and energy consumption structure optimisation, but taxes have small negative effects on economic growth (Lu, Tong et al. 2010, Chi, Guo et al. 2014). Nevertheless, a carbon tax may not effectively or efficiently induce anticipated socioeconomic and environmental outcomes considering the complicated socioeconomic connections or stringent environmental issues. Hence, it is important that a holistic and general model should be employed to simulate the whole economic system and related environmental issues to fully explore the policy effects of a carbon tax (Khastar, Aslani et al. 2020). Unfortunately, a great deal of previous research, which evaluated carbon taxes using microeconomic models, only focused on a specific sector or even a company (Almutairi and Elhedhli 2014, Martin, de Preux et al. 2014). These evaluations of carbon taxes could be accurate on a targeted sector or company; however, the evaluations could be biased on a holistic view. The biased evaluations are likely to reduce the governmental willingness of policy implementation.

Previously, the biased evaluation of a carbon tax is mainly caused by using the partial equilibrium (PE) approach, where one or a few closely related markets are researched (Farrow and Rose 2018). For example, Doda and Fankhauser (2020) used a partial equilibrium model to evaluate the supply-side distributional consequences of climate policies; Kersting, Duscha et al. (2018) used a partial equilibrium model to analyse the impact of shale gas on the policy costs. Although the partial equilibrium models in the above research could elaborate the role of a specific policy in some sectors (Sugiyama, Akashi et al. 2014), the results of the PE approach could be biased as this approach cannot capture the whole picture of the complicated socioeconomic intra- and inter-connections.

In contrast, the general equilibrium (GE) approach considers all the potential sectoral interactions at the cost of relying on a more aggregated and abstract level of analysis (Gohin and Moschini 2006). In other words, the GE approach fully considers the impacts of a shock on all the markets within a given area over a certain period even though it is more difficult to interpret the results. The GE approach is criticised for the lack of micro theoretic foundations (Farrow and Rose 2018). But if interpreted appropriately in details, the results of the GE approach are much more trustworthy. In this chapter, the GE approach is adopted to comprehensively analyse the socioeconomic effects of the carbon tax in China.

In the GE approach, Computable General Equilibrium (CGE) models have been widely used to study a carbon tax. CGE models stem from the general equilibrium theory of Walras, which implies that the aggregated supplies and demands are equalised across all the interconnected markets in the economy (Xie, Dai et al. 2018). To some extent, the advent of CGE models intensified the study of macroeconomic "closure," or the reconciliation of the macroeconomic and multisectoral perspectives (Robinson and Rolandholst 1988). In other words, CGE models depict the reality by incorporating all the endogenous variables in a series of equations. Therefore, CGE model results could be much closer to the reality than the results of a PE model. Owing to the capacity and applicability of modelling socioeconomic phenomena, CGE models have already become standard and useful tools in policy simulations or evaluations (Guo and Liu 2016, Li and Jia 2017, Li, Dai et al. 2018).

Although CGE models originated from the pioneering work of Johansen (1960), however, the first CGE model that analysed the impacts of a carbon tax was in Hudson and Jorgenson (1974). Since then, CGE models have become popular tools to evaluate socioeconomic impacts of a carbon tax (Wang, Huang et al. 2020). Recently, CGE models have been used to evaluate the potential impacts of carbon pricing at the macro level (Li and Su 2017). This is because multisectoral CGE models incorporate macro variables and economic mechanisms for achieving balance among aggregates (Robinson and Rolandholst 1988).

Previously, researchers often used static CGE models to evaluate the policy effects of a carbon tax (Guo, Zhang et al. 2014, Chen, Zhou et al. 2017, Li and Jia 2017). As static or standard CGE models can only show the interrelations of macro variables in the short term (usually one year), they are not applicable for dynamic analysis in the long term. Hence, static CGE models are not well-adapted to measuring the macroeconomic effects of governmental policies, which usually last for more than one year (Bhattarai, Bachman et al. 2018). Also, static CGE models are criticised for the analytical inconsistency, as adjustments are assumed to occur spontaneously (Babatunde, Begum et al. 2017). In the reality, economic variables could vary in a time order, and feedbacks exist after the occurrence of a shock.

This chapter contributes to the literature by employing a dynamic recursive CGE model to study the policy effects of the Chinese carbon tax. A dynamic CGE model captures the accumulative characteristics of an economic activity and thus increases the mid/long term predictive capabilities of the simulations (Chi, Guo et al. 2014). Compared to a static CGE model, a dynamic recursive CGE model has an additional dynamic block to capture how the variables change over time. In addition, within the CGE framework, the detailed disaggregation of the electricity sector separates the subsectors exploiting fossil fuels from those exploiting renewables. This disaggregation protects the development of renewable energies from the adverse effects of the simulated carbon tax.

Method

In this chapter, the structure of the CGE model is mainly based on Guo, Zhang et al. (2014) who investigated the policy effects of the Chinese carbon tax based on China 2010 Input–Output Table. The CGE model in this paper is run by the GAMS software. The GAMS code of this chapter is built basing on Zhang et al. (2014) who generously shared the GAMS code of their CGE model in the supplementary material of their published paper. Starting from the GAMS code in this chapter, the GAMS codes of the other chapters are built by adding additional equations or changing the optimal condition.

To construct the CGE model in this chapter, the top-down method is adopted, because it considers initial market distortions, pecuniary spill-overs, and income effects on various economic agents from an economy-wide perspective. In contrast, the bottom-up method neglects the macroeconomic impacts of simulated policies (Bohringer and Rutherford 2008). Although the hybrid of top-down and bottom-up allows an analyst to exploit the advantages of the top-down and bottom-up method, the dimensionality problem imposes limitations on the practical application (Bohringer and Rutherford 2008). Nevertheless, the top-down method lacks details in current and future technological options (Bohringer and Rutherford 2008). I will model the technical impact of the carbon tax later in the fourth chapter.

The CGE model in this chapter includes two regions (China and the rest of the world) and four economic entities (the representative household, enterprise, foreigner, and government). As this chapter is intended for an environmental issue, an environment block is included in the CGE model. The sector division of the Chinese economy is shown in Table A1.1 in Appendix A. According to Table A1.1, there are 42 sectors in the 2015 China Input-Output Table, and 21 sectors are left through the aggregation and disaggregation process in this chapter.

1. Production Block

In the production block, the top level is formed by a Leontief combination of intermediate inputs and added values, while the lower levels are modelled by constant elasticity of substitution (CES) functions. Eq. (1.1) shows the polynomial expression of a CES function, where F_1 and F_2 refer to the input of Factor 1 and Factor 2 respectively; $SGDP_i$ is the output of Sector i by using Factor 1 and Factor 2; $scale$ is the scale parameter; $ShrF_1$ is the share of F_1 in the production; ρ_f denotes the elasticity parameter between F_1 and F_2.

$$SGDP_i = scale * (ShrF_1 * F_1^{\frac{\rho_f - 1}{\rho_f}} + (1 - ShrF_1) * F_2^{\frac{\rho_f - 1}{\rho_f}})^{\frac{\rho_f}{\rho_f - 1}} \tag{1.1}$$

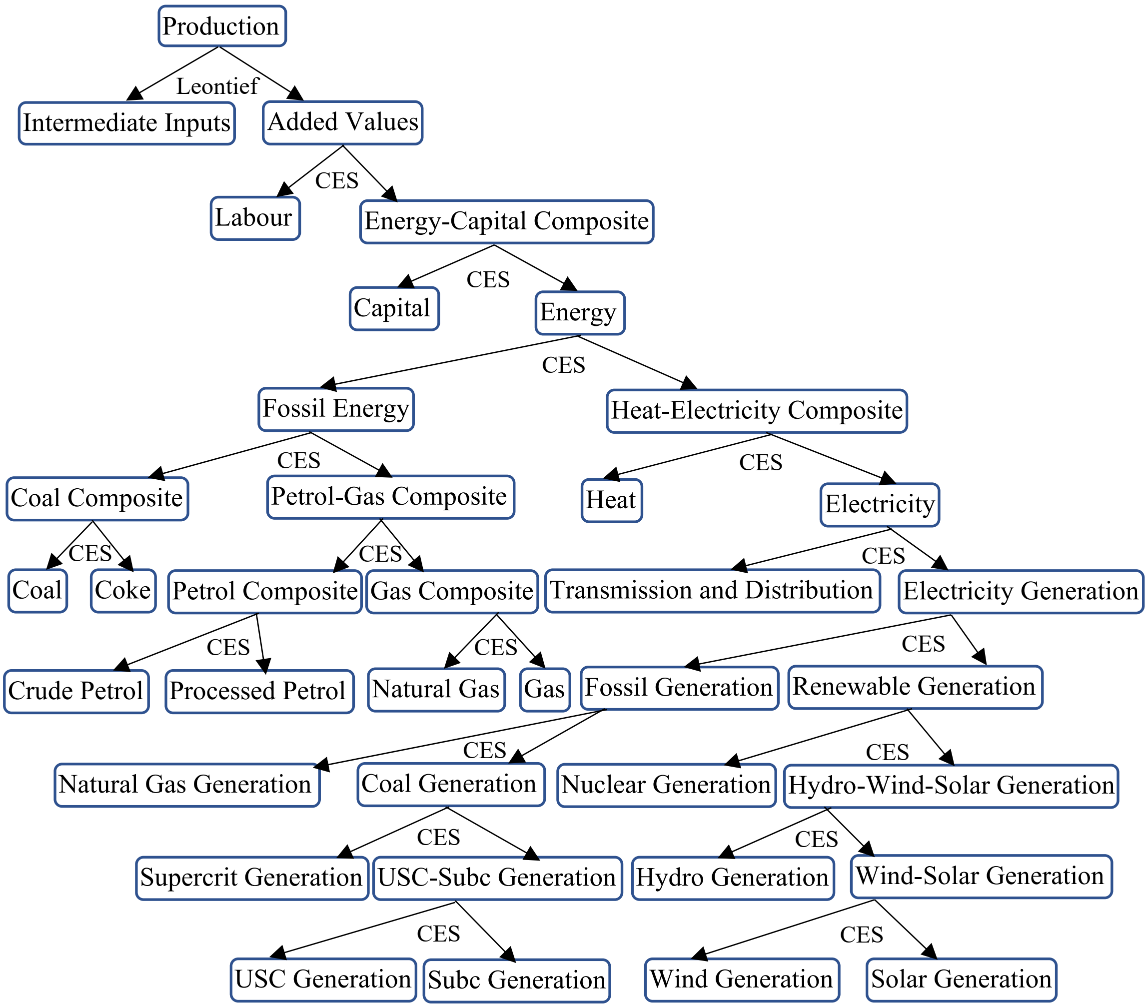


Fig. 1.1 The Structure of the Production Block

Fig. 1.1 shows the structure of the production block using the top-down method. In Fig. 1.1, the elasticity parameters in the CES functions are from Guo, Zhang et al. (2014), and their values are shown in Table A1.2 in Appendix A. Noticeably, the elasticity parameters of the electricity subsectors in this chapter are assumed to be the same as the elasticity parameter of the electricity sector given in Guo, Zhang et al. (2014). The influence of the elasticity parameters on the model equilibrium will be assessed by the sensitivity analysis to find out how reliable the results are.

A carbon tax or ETS policy will increase the costs of the nonrenewable energy inputs, and thus the quantities of the nonrenewable energy inputs will decrease. If the elasticity parameters are fixed, a decrease in the energy inputs will reduce the national output even if the nonenergy inputs are the same.

2. Income-Expenditure Block

In this block, a representative household and enterprise are introduced to represent the entire Chinese households and enterprises respectively. The household consumes either the domestic or foreign goods, whilst its income is determined by the labour, capital, and money transfers. By comparison, the enterprise's income only comes from the capital source, whereas its expenditure includes the tax payments to the government and money transfers to the household.

International labour migration and capital flow will complicate the CGE model structure, but their magnitudes are relatively small compared to the overall labour supply and capital investment, according to the NBS (2017) data. Hence, the labour and capital are assumed to be immobile across regions in this chapter. The sectoral move of labour and capital within the country may incur training and installation costs respectively, which are likely to affect the CGE model results. The NBS (2017) data have shown that the unemployment rate was 3.30%, and the other costs occupied 11.16% of the total investments on fixed assets in 2015. The CGE model could have quantified the unemployment and other costs at the price of the reduction in the degree of freedom. With a small sample size, I have simplified the complicated real world by assuming that the labour and capital are perfectly mobile across the sectors with no transaction costs.

The simulated carbon tax may cause the flow of the labour or capital between the sectors, but the summation of the labour or capital is assumed to equal that in the baseline scenario where no carbon tax is imposed. The sectoral output is defined as the summation of the sectoral depreciation of fixed capital (DFC), compensation of employees (CE), net tax subsidies on production (NTSP), and operating surplus (OS) in 2015 China Input-Output Table. CE is the labour income. The summation of DFC and OS is the capital income. NTSP is the production tax. The summation of the sectoral output denotes the real GDP (RGDP) of the country. In this chapter, the output tax refers to the carbon tax imposed on the sectoral output of the energy sectors except for the electricity subsectors exploiting renewables.

3. Government Block

This block mainly focuses on the economic behaviours of a representative government which plays the entire roles of the local and central governments in China. The governmental income comes from the taxes imposed on the consumption, production, international trade, and carbon emissions. The government spends its income on the consumption, money transfers, and savings. The governmental spending is formed by a CES utility function. The collected revenues from the carbon tax could be recycled to three economic entities: the government, household, and enterprise. There are no officially published data of the governmental energy consumption. Perhaps, this is because the governmental energy consumption is very small compared to the household and enterprise consumption. Hence, the governmental energy consumption and thus its emissions are assumed to be zero in this chapter.

4. Trade Block

In this block, the rest of the world (RW) produces goods consumed by the household, and it consumes goods imported from the enterprise. Trade balance is assumed when the export monetary value equals the import value. The exchange rate of the Chinese currency is exogenously determined as it is mainly affected by the RW. The trade function is based on the Armington (1969) assumption that goods produced in different regions are imperfect substitutes. Profit maximisation drives the enterprise to sell its goods either in the domestic or foreign market. This production choice is expressed using a constant elasticity of transformation (CET) function (Ge and Lei 2017). The CET function has the same mathematic formula as the CES function, but the exponent of the CET function must be larger than 1 to ensure that the Production Possibility Frontier (PPF) is convex to meet the Armington Assumption. The CET function is shown in Eq. (1.2).

$$QA_i = scaleCET_i * (ShCET_i * QE_i^{\frac{\rho_{CET,i}-1}{\rho_{CET,i}}} + (1 - ShCET_i) * QDA_i^{\frac{\rho_{CET,i}-1}{\rho_{CET,i}}})^{\frac{\rho_{CET,i}}{\rho_{CET,i}-1}} \tag{1.2}$$

In Eq. (1.2), QA_i is the total domestic production of the Commodity i; $scaleCET_i$ is the CET scale parameter of Commodity i; $\Delta ShCET_i$ is the share of the export in the domestic production for Commodity i; QDA_i is the domestic consumption of the domestically produced Commodity i; $\rho_{CET,i}$ is the elasticity parameter between the domestic consumption and export for Commodity i.

However, the Armington assumption was criticised for three main drawbacks: difficulties in determining output prices in multi-region models with IO tables that permit interregional trade in intermediate goods; difficulties in measuring the number of unknown factor prices whose equilibrium values need to be determined simultaneously; difficulties in estimating the substitution elasticity between goods from different regions for small regions (Plassmann 2005). In this chapter, the CGE model is mainly targeted at the connection between China and the RW through the trade and money transfers, but there are no multiple-region specific households or sectors. Labour, capital, and energy are the three main production factors, and technology is introduced as an influential factor in the fourth chapter. The CGE model enables the prices of the production factors to be determined simultaneously when the optimal condition is reached. The two regions (China and RW) are both large, and there are no issues of estimating elasticities in small regions. Hence, the aforementioned three drawbacks of the Armington assumption will not be of great concern in this chapter.

5. Environmental Block

Originating from Dufournaud, Harrington et al. (1988), an environmental CGE model usually has an additional environmental block, compared to a traditional CGE model. In the environmental block of the CGE model in this chapter, when no carbon tax is imposed, the carbon emissions from the household and sectoral energy consumption affect the air quality, thereby impairing the labour health and reducing the effective labour supply. On the contrary, the carbon tax imposed on the outputs of the nonrenewable energy sectors may induce the deadweight loss, the magnitude of which is measured by the Hicksian equivalent variation (Zhang 1998). However, the tax may also decrease the nonrenewable energy exploitation and thus abate the carbon emissions, which may increase the labour health. According to Choi, Liu et al. (2017), the anthropogenic emissions are calculated using Eq. (1.3), where EC_{ij} is the consumption of Energy j in Sector i; α_j is the carbon emission factor of Energy j, according to IPCC (2006).

$$E_j = \sum_i EC_{ij} * \alpha_j \tag{1.3}$$

6. Model Closure

In this block, three conditions are applied to the model closure. Firstly, the market clearance means no free disposability; this is to say, the flows of the goods and factors must be absorbed by the production and consumption within and beyond the economy (Sue Wing 2004). Secondly, the zero profit implies the constant returns to scale in the production and perfectly competitive markets for the produced commodities (Sue Wing 2004). Thirdly, the income balance denotes that all the entities within and beyond the economy exhaust their incomes, but deficits are not allowed.

7. Dynamic Block

In this chapter, the exogenously determined dynamic variables are the population, price, energy consumption growth rate, output growth rate, and capital accumulation. The projected Chinese population will follow the medium variant scenario in 2017 World Population Prospects (WPP) by UN (2017). The export price is assumed to change proportionally to the price projection of the total OECD countries by OECD (2014), whereas the GDP deflator, domestic commodity price, and import price will change proportionally to the price projection of China by OECD (2014). All the prices in the base year 2015 are assumed to be one. The projected energy consumption growth rate is from the reference scenario in 2017 International Energy Outlook by EIA (2017). The output growth of the energy sectors will follow the projected growth of the energy consumption, whilst the output growth of the nonenergy sectors will follow the regional GDP long-term forecast by OECD (2018). The projected physical capital stock will follow Long and Herrera (2016), whilst the projected human capital stock is based on the annual China Human Capital Report published by China Centre for Human Capital and Labour Market Research (CHLR). Appendix C shows the projections of the exogenous variables mentioned above in details.

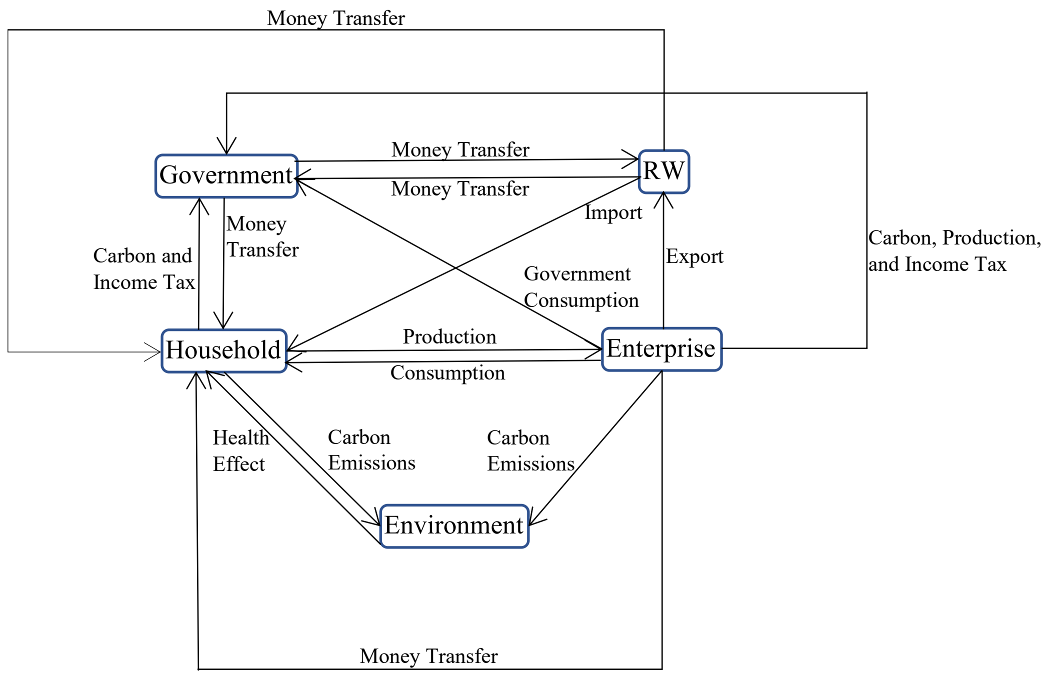


Fig. 1.2 The Framework of the CGE Model

Fig. 1.2 shows the structure of the CGE model defined in this chapter. In Fig. 1.2, the connections among the economic entities and the environment are denoted by the arrows. The equations underneath the arrows are displayed in Appendix B.

The database of a CGE model is usually drawn from a Social Accounting Matrix (SAM), which is mainly based on an input-output table. A SAM, which highlights the circular flows of payments within a system, is a simple and efficient way of representing the fundamental law of the economics that "for every income, there is a corresponding outlay or spending (Karimsakov and Karadag 2017). A SAM also provides a comprehensive and consistent description of the transactions in a given year (Karimsakov and Karadag 2017). A SAM captures the interrelations among the economic activities, production factors, and institutions, but it ignores the interactions between the economy and environment (Xie 2000).

When studying environmental issues, researchers tend to use an environmental CGE model which is based on an environmental Social Accounting Matrix (ESAM). However, in this chapter, the CGE model is built on a traditional SAM to analyse the policy effects of the carbon tax. This is because the environmental impacts of the tax are modelled in the environmental block of the CGE model. To build the SAM, I have used the 2015 China Input-Output Table as the starting point. The sectoral labour input is equal to the sectoral labour income divided by the corresponding average wage, whilst the sectoral and household energy consumption data are from China Energy Statistical Yearbook by NBS (2016).

In this chapter, the carbon emission factors (CEFs) have been calculated according to IPCC (2006), shown in Table 1.1. However, the CEFs of the liquid energies need to be adjusted by the density parameters. This is because the units of the liquid energy CEFs are kg CO_2/L, while the units of the liquid energy consumption in China Energy Statistical Yearbook are 10^4 t.

Table 1.1 The Carbon Emission Factors (CEFs)

Energy	Coal	Coke	Crude Oil	Kerosene	Gasoline	Diesel Oil
Unit	t CO_2/t	t CO_2/t	t CO_2/t	t CO_2/t	t CO_2/t	t CO_2/t
CEF	1.98	3.18	3.63	3.92	4.29	3.78
Energy	Fuel Oil	Natural Gas	TD	Supercrit	USC	Subc
Unit	t CO_2/t	t CO_2/10 M^3	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh
CEF	3.64	19.98	0.0062	22.10	20.19	15.15
Energy	NG	Nuclear	Hydro	wind	solar	
Unit	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	t $CO_2/10^4$ kwh	
CEF	22.39	0	0	0	0	

Table 1 shows the calculated CEFs in this chapter. Noticeably, the electricity generating from the renewables is assumed to have zero CEFs, whilst the electricity transmission and distribution (TD) has a very low CEF. This is because the TD consumes the electricity generating from the nonrenewable energies.

According to NBS (2016) data, the electricity sector accounted for about 25% of the Chinese anthropogenic emissions in 2015. Previously, electricity was regarded as a clean energy from the consumption perspective (Guo, Zhang et al. 2014), and thus a carbon tax imposed on the energy consumption usually exempts the electricity consumption. However, the electricity generation does emit greenhouse gases, which suggests the need for levying taxes on the generation. A crowding-out effect may arise from the taxation on the energy from the consumption perspective. This is because a rational economic entity will consume more electricity when the prices of fossil fuels rise induced by the taxation. Considering that approximately 75% of the Chinese electricity was generated from fossil fuels in 2015, the taxation may unexpectedly increase the consumption of fossil fuels in the electricity generation stage. In contrast, a carbon tax imposed on the electricity generation may avoid the crowding-out effect. This is because the emissions of the electricity, an entity consumes, are linked to the carbon dioxide emitted at the generation stage. From the generation perspective, the emissions of the electricity sector are the emissions in the generation of the self-consumed electricity only.

The disaggregation of the electricity sector is needed in the carbon taxation because some electricity subsectors mainly exploit renewables and thus emit almost no carbon dioxide. In contrast, the other electricity subsectors combust fossil fuels and thus emit large quantities of greenhouse gases. Without disaggregation, all the electricity subsectors are faced with the same tax rate, and consequently those who use renewables may be stuck in an unfavourable situation. Electricity disaggregation within the framework of a CGE model dates back to Wing (2006) who disaggregated the US electricity sector to analyse the general equilibrium effects of the US climate policy. In the China case, Lindner, Legault et al. (2013) disaggregated the Chinese electricity sector in the 2007 input-output table using the regional data. In this chapter, I have followed the disaggregation approach in Lindner, Legault et al. (2013) to implement the carbon tax fairly for the electricity subsectors exploiting renewables only. In

Table A1.3 in Appendix A, the electricity sector is decomposed into eight generation subsectors and one transmission and distribution (TD) subsector. Therefore, there are 21 sectors in the un-disaggregated model, whilst there are 29 sectors in the electricity-disaggregated model.

According to 2016 China Electric Power Yearbook (CEPY) published by CEPY Editor Association (2016), the Chinese power generation and grid investment in 2015 took up 45.9% and 54.1% of the electricity sectoral output respectively. Hence, the TD subsector output is assumed to occupy 54.1% of the electricity sectoral output, whilst the output of the generation subsectors altogether occupies 45.9% of the electricity sectoral output. The energy consumption of the electricity sector is divided as: the coal consumption is assumed to be in the three coal generation subsectors based on the output; the oil consumption is assumed to be divided among the subsectors exploiting nonrenewable energies according to Lindner, Legault et al. (2013); the gas consumption is assumed to be in the gas generation subsector only. The consumed electricity in the TD subsector is from the generation subsectors according to the sectoral electricity consumption mix in Lindner, Legault et al. (2013). A generation subsector is assumed to consume the electricity only generated from its own. The nuclear, hydro, wind, and solar generation subsectors are assumed to exploit renewables only and thus have no emissions.

In this chapter, the simulated carbon tax is imposed on the outputs of the sectors that produce nonrenewable energy. As the nonrenewable energy production becomes less profitable under the carbon tax, less renewable energy will be produced. Although the outputs of the nonenergy sectors are not directly affected by the carbon tax, the nonenergy sectors will face a shortage of the energy inputs, and thus their outputs are indirectly affected. In addition, the shortage of the energy inputs will increase the energy price, and thus the nonenergy sectors will pay more to use the nonrenewable energy. Hence, the outputs of the nonenergy sectors are indirectly affected by the carbon tax. Because of the reduction in the nonrenewable energy consumption, the output tax will finally reduce the sectoral carbon emissions.

Compared to a Pigouvian tax imposed on the energy consumption directly, owing to its indirect effect on the energy exploitation, an output tax may encounter less oppositions from the nonenergy sectors, whilst the nonrenewable energy sectors may suffer more income loss as their outputs are directly taxed. Noticeably, under an output tax, a rational entity could use more imported fossil fuels because of the tax-induced energy shortage. Hence, in this chapter, the imported fossil fuels are assumed to be not affected by the carbon tax, considering that China’s energy import is mainly controlled by the government to ensure the energy security (Wu 2014).

If implemented alone, the carbon tax belongs to the domain of first-best climate policies which rarely induce the optimum change of social welfare owing to the socioeconomic constraints in the reality. As first-best climate policies might not be socioeconomically advantageous, in this chapter, a second-best climate policy is simulated where the tax revenues are recycled to an economic entity (the household, government, or enterprise) as the complementary policy of the carbon tax. Some researchers emphasised the importance of recycling the tax revenues as a complementary policy. For example, Liu and Lu (2015) used a dynamic CGE model to study the economic impacts of different carbon tax revenue recycling schemes in China, arguing that carbon revenue recycling schemes were important in designing the carbon tax; Xiao, Niu et al. (2015) utilised a dynamic recursive multi-sector CGE model to explore the policy effects of the environmental tax in China, concluding that the governmental refund of the tax could relieve the negative effects of the tax. Because of the unique policy design in this chapter and the consideration of the influential factors in the next chapters, the socioeconomic impacts of recycling the tax revenues could be very different in this paper from the previous research.

Finally, a sensitivity analysis is performed to test the uncertainties of the parameters on the model results. This is because a sensitivity analysis answers how sensitive the equilibrium values of the economic variables are subject to the choice of the fundamental parameters (Hermeling, Loschel et al. 2013). In a CGE framework, a sensitivity analysis is crucial because it is helpful to understand how the specific model works and respond to the critics of the 'black box' in the CGE analysis (Antimiani, Costantini et al. 2015). In this chapter, the sensitivity analysis is performed on the uncertainties of the elasticity parameters, namely the elasticities of substitution. This is because the elasticities between energy and other inputs and among fuels are the most important parameters that affect the CGE results (Lu and Stern 2016). Unfortunately, "in the economic literature, there is little consensus about different elasticities for energy products" (Bhattacharya 1996). Hence, it is crucial to test how sensitive the model results are to the uncertainties of the elasticity parameters.

The elasticity parameters used in this chapter are from Guo, Zhang et al. (2014) who complied the elasticities in the previous research. In the sensitivity analysis, all the elasticity parameters are assumed to change by 50%, 20%, 10%, -10%, -20%, and -50% to study to what extent the elasticity parameters affect the model equilibrium. In the range of ±50%, the inputs in some sectors may turn from poor (good) substitutes to good (poor) substitutes (Lu and Stern 2016). In general, the high elasticity parameters imply that an economy is flexible, while the low elasticity parameters imply that an economy is stringent.

To decompose the real GDP (RGDP) changes resulting from the elasticity parameter changes, I have used the Logarithmic Mean Divisia Index (LMDI) method following Lu and Stern (2016). Dating back to Ang and Liu (2001), the LMDI decomposition method is preferred in the literature as it has no unexplained residuals (Ang 2004). The LMDI decomposition in this chapter is shown in Eq. (1.4).

$$\frac{\Delta RGDP}{RGDP_{BAU}} = \frac{\Delta RGDP}{\Delta E} \times \frac{\Delta E}{E_{BAU}} \times \frac{E_{BAU}}{RGDP_{BAU}} \tag{1.4}$$

In Eq. (1.4), $\Delta RGDP$ is the absolute RGDP change under the carbon tax compared to the baseline scenario; $RGDP_{BAU}$ is the baseline RGDP; ΔE is the absolute emission change under the tax compared to the baseline scenario; E_{BAU} is the baseline carbon emissions. According to Eq. (1.4), the RGDP relative change $\frac{\Delta RGDP}{RGDP_{BAU}}$ could be decomposed into three parts: $\frac{\Delta RGDP}{\Delta E}$ is defined as the average mitigation cost; $\frac{\Delta E}{E_{BAU}}$ is the relative emission abatement; $\frac{E_{BAU}}{RGDP_{BAU}}$ is the baseline carbon intensity.

I have defined $g = \frac{\Delta RGDP}{RGDP_{BAU}}$, $C = \frac{\Delta RGDP}{\Delta E}$, $A = \frac{\Delta E}{E_{BAU}}$, and $I = \frac{E_{BAU}}{RGDP_{BAU}}$. Eq. (1.5) is obtained using the LMDI method, where $\Delta C_k = \frac{g_k - g_d}{ln\frac{g_k}{g_d}} \times ln\frac{C_k}{C_d}$, $\Delta A_k = \frac{g_k - g_d}{ln\frac{g_k}{g_d}} \times ln\frac{A_k}{A_d}$, and $\Delta I_k = \frac{g_k - g_d}{ln\frac{g_k}{g_d}} \times ln\frac{I_k}{I_d}$. In Eq. (1.5), the subscript k denotes the k set of the elasticity parameters, and d is the default set of the elasticity parameters. If Eq. (1.5) is divided by g_d, the relative parametric impact on the RGDP is shown in Eq. (1.6).

$$\Delta g_k = g_k - g_d = \Delta C_k + \Delta A_k + \Delta I_k \tag{1.5}$$

$$\frac{\Delta g_k}{g_d} = \frac{\Delta C_k}{g_d} + \frac{\Delta A_k}{g_d} + \frac{\Delta I_k}{g_d} \tag{1.6}$$

Scenarios

Recently, with increasing recognition of the significant of carbon taxes, researchers are interested to evaluate whether the carbon tax is an effective tool for China to accomplish the win-win targets of emission reductions and GDP growth (Liu, Bai et al. 2021). Hence, I have analysed the emission reduction and welfare effects of the designed carbon tax in this chapter.

The tax rate is one of the key factors that determine the policy effects of a carbon tax (Liu, Bai et al. 2021). In this chapter, the carbon tax is defined basing on the fixed percentage tax rate rather than the fixed amount of the tax price. This is because the baseline Chinese carbon emissions will increase steadily over the period 2015–2030. A fixed amount of the tax price may achieve a larger proportion of the emission reduction when the emissions were lower at the beginning, but it may achieve a lower proportion of the emission reduction when the emissions will be higher at the end of the period. Hence, designing the carbon tax basing on the fixed percentage tax rate is more meaningful as the tax will regulate the carbon emission evenly over the research period.

I have designed three fixed percentage tax rates of the carbon tax, namely the 1%, 2%, and 3% tax, which is equivalently to 2.4–4.9, 3.6–7.8, and 4.4–9.8 $\$/t\ CO_2$ over the research period. According to Li and Jia (2017), the National Development and Reform Commission and the Ministry of Finance of China has published the guidance for the ideal tax rate, where the low, medium, and high tax rate are 1.7, 4.2, and 6.7 $\$/t\ CO_2$ respectively. Hence, the 1% tax in this chapter will vary around the medium tax rate; the 2% tax will vary between the medium and high tax rate; the 3% tax will vary around the high tax rate.

Table 1.2 The Designed Scenarios and Their Main Features in This Chapter

Scenarios	Electricity Disaggregation	Tax Imposition	Complementary Policy of Tax
Production Model	No	NA	NA
Consumption Model	No	Output of Nonrenewable Energy Sectors	NA
Electricity Model (Output Tax)	Yes	Output of Nonrenewable Energy Sectors	No
Pigouvian Tax	Yes	Consumption of Nonrenewable Energies	NA
Tax Recycling	Yes	Output of Nonrenewable Energy Sectors	Yes
Marginal Policy Effect	Yes	Output of Nonrenewable Energy Sectors	NA

Note: NA means not applicable in the scenario

Table 1.2 summarises the designed scenarios in this chapter. To begin with, I compare the 2015 sectoral and household emissions from the electricity consumption and production perspective in the consumption and production model in the baseline scenarios. In the consumption model, the electricity sector has the emissions of the self-consumed electricity, whilst in the production model, the electricity has the emissions of all the generated electricity. At the 1% tax, the electricity sector in the consumption model is disaggregated into nine subsectors, and the disaggregated model is called the electricity model. The 1% tax is not imposed on the electricity subsectors exploiting renewables in the electricity model. In contrast, in the consumption model, all the electricity subsectors are confronted with the same tax rate, which is unfair to the electricity subsectors exploiting renewables. Noticeably, in these two models, the economic and emission indicators at the country level in the baseline scenario are assumed to be the same.

In the electricity model, the carbon tax is imposed on the output of the sectors producing nonrenewable energies, and thus the tax is an output tax. I compare the policy effects of the 1% output tax with the 1% Pigouvian tax. In the aforementioned carbon tax, the tax revenues are assumed to be kept in the governmental budget. However, the tax revenues could be also recycled to the household or enterprise, and thus I have studied how the revenue recycling will influence the policy effects of the carbon tax. Finally, the marginal policy effects of the 1%, 2%, and 3% output tax are also analysed in this chapter.

In the Intended Nationally Determined Contribution (INDC) target, China has promised to peak its emissions around 2030 and make the best effort to peak early; lower its emissions per unit of GDP by 60% to 65% from the 2005 level by 2030 (NDRC 2015). I will check whether the carbon tax will help China meet its INDC target.

Model Results

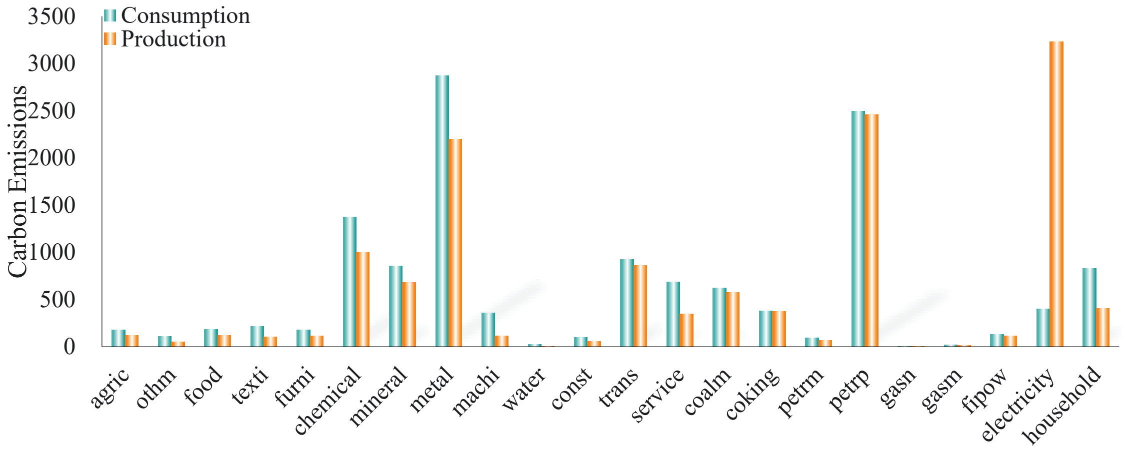


Fig. 1.3 The 2015 Sectoral Emissions in the Consumption and Production Model (Unit: 10^6 t)

Fig. 1.3 shows the distribution of the sectoral and household emissions in 2015. From the electricity production perspective (production model), the electricity sector had the largest emissions, whilst the metal sector had the largest emissions from the electricity consumption perspective (consumption model). In both models, the petroleum processing sector had the second largest emissions.

Fig. 1.4 The Comparison of the 2015 Sectoral and Household Emissions

Fig. 1.4 shows the percentage comparison of the emissions from the electricity consumption and production perspective. In the consumption model, the household and sectors had more emissions except that the electricity sector only had the carbon emissions from the self-consumed electricity in 2015. The significant differences of the sectoral emissions between the two models imply that the carbon emissions from the electricity generation played a very important role in the total emissions of China. As the production model overlooks the genuine emissions of an economic entity, I have calculated the sectoral and household emissions using the consumption model.

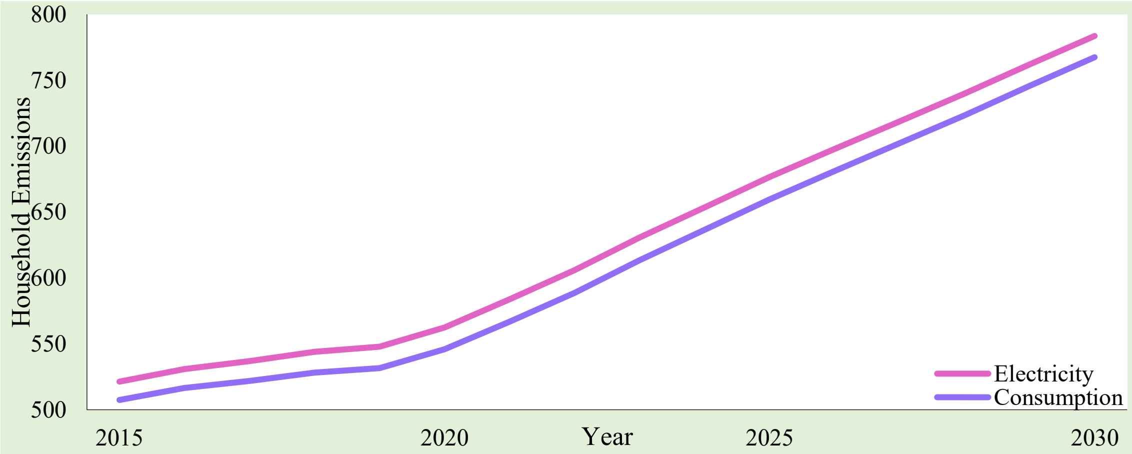
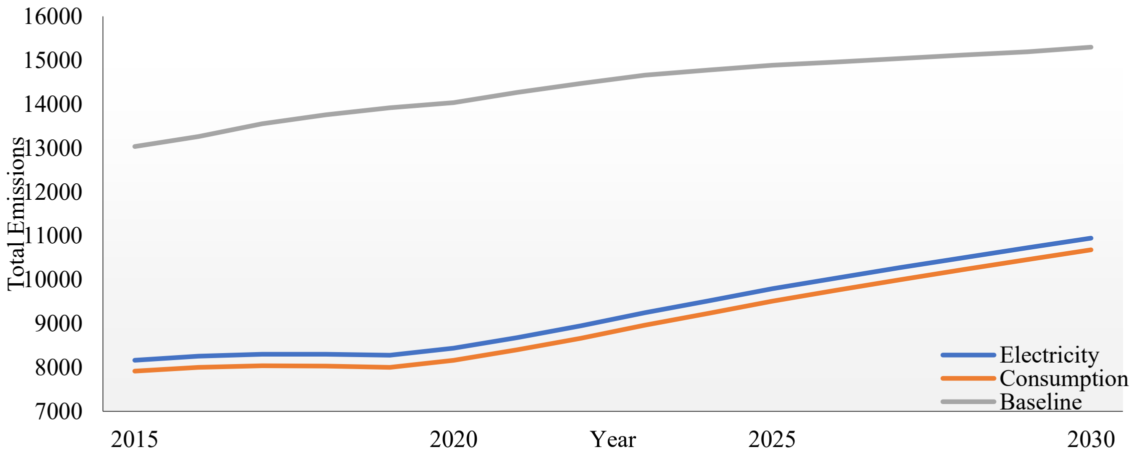


Fig. 1.5 The Comparison of the Household Emissions at the 1% Tax (Unit: 10^6 t)

Fig. 1.5 shows the comparison of the household emissions in the consumption and electricity model, where the electricity sector is disaggregated. At the 1% tax, the household emissions in the electricity model will be slightly higher than that in the consumption model, and the gap between the two models will remain stable over time. Generally, the household emissions in the electricity model are approximately 5% higher than that in the consumption model. Fig. A1.1 in Appendix A shows the household emissions in the baseline scenario where the emission gap between the two models will be smaller.



Note: "Baseline" denotes the baseline scenario in the two models; "Consumption" and "Electricity" denote the 1% tax scenario in the consumption and electricity model respectively.

Fig. 1.6 The Total Emissions in the Consumption and Electricity Model (Unit: 10^6 t)

Fig. 1.6 shows how the total emissions will change over the studied period in the consumption and electricity model. In the baseline scenario, the total emissions will be the same in these two models. The 1% tax will reduce approximately 40% of the total emissions in both models, compared to the baseline scenario. However, the tax will induce the lower total emissions in the consumption model. This is because the electricity subsectors exploiting renewables are regulated by the carbon tax in the consumption model but not regulated in the electricity model. Fig. A1.2 in Appendix A shows that the tax will have almost no effect on the carbon intensity in these two models.

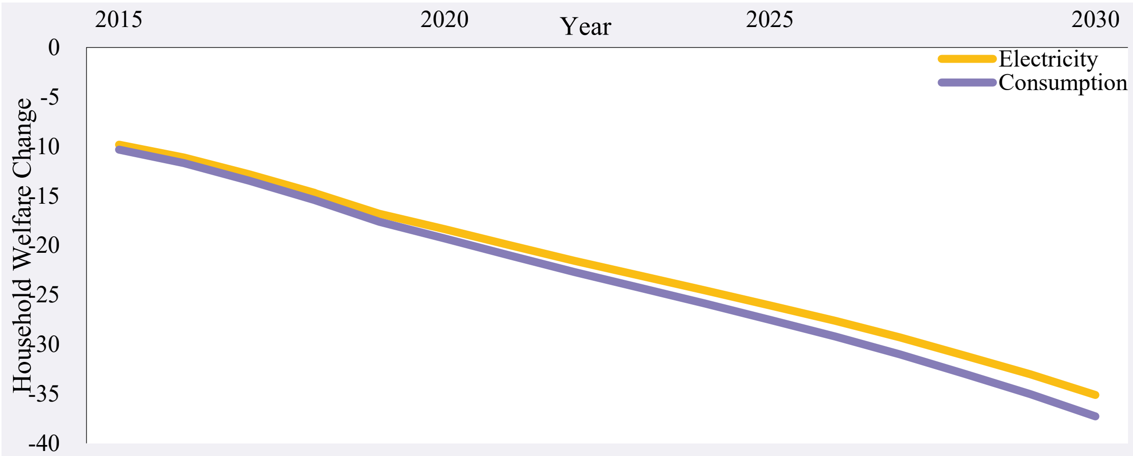


Fig. 1.7 The Household Welfare Change in the Consumption and Electricity Model (Unit: 10^{12} CNY)

Fig. 1.7 shows how the 1% tax will affect the household welfare in the consumption and electricity model over the research period. In both models, the household welfare will deteriorate, but the welfare will decrease more in the consumption model. The gap of the welfare change between the two models will expand over time, but the difference is less than 2%. More welfare loss induced by the tax in the consumption model corresponds to the fact that the electricity subsectors exploiting renewables are regulated by the tax in the consumption model. Fig. A1.3 in Appendix A shows the real GDP (RGDP) change at the 1% tax compared to the baseline scenario. The RGDP change is very similar to the household welfare change: the tax will reduce the RGDP in both models and induce more deadweight loss in the consumption model.

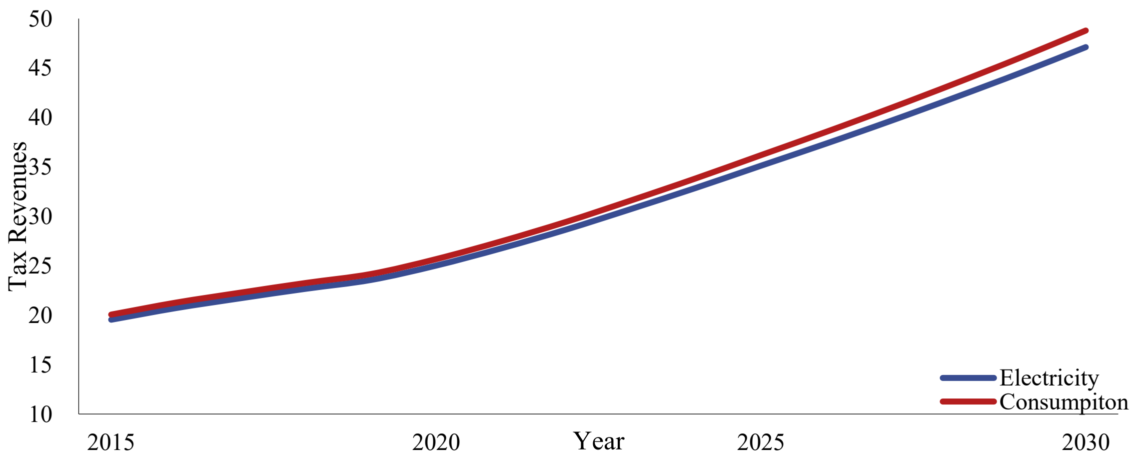


Fig. 1.8 The Tax Revenues in the Consumption and Electricity Model (Unit: 10^9 CNY)

Fig. 1.8 shows the fluctuations of the tax revenues at the 1% tax over time in the consumption and electricity model. According to Fig. 1.8, in the consumption model, more tax revenues will be collected, which means the more governmental intervention on the market mechanism. This is because the electricity subsectors exploiting renewables are regulated by the tax in the consumption model, but they are not regulated in the electricity model. Hence, the 1% carbon tax will induce more welfare loss in the consumption model, shown in Fig. 1.7 and A1.3.

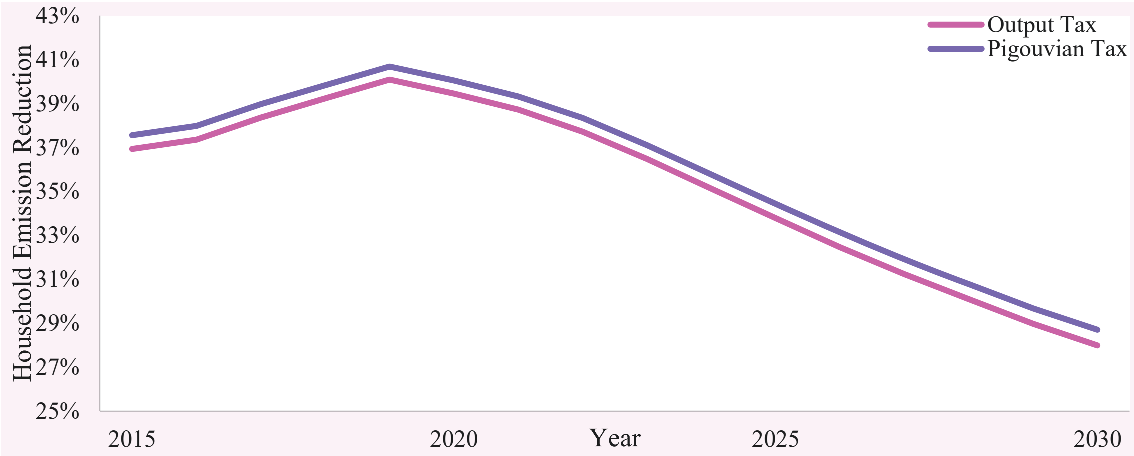


Fig. 1.9 The Household Emission Reduction under the Output and Pigouvian Tax

Fig. 1.9 shows the policy effect of the output and Pigouvian tax on the household emissions over time. According to Fig. 1.9, compared to the baseline scenario, both taxes will reduce the household emissions significantly. The policy effect increased in 2015–2019 but will decrease during 2020–2030. The output tax will induce approximately 1% less household emission reduction than the Pigouvian tax, and the gap between the two taxes will remain stable over the research period.

Fig. A1.4 in Appendix A shows the total emission reduction under the output and Pigouvian tax. According to Fig. A1.4, the total emissions will follow a very similar trend to the household emissions. However, the output tax will induce roughly 0.1% more total emission reduction than the Pigouvian tax, even though the gap between the two taxes is minimal. Similarly, Fig. A1.5 in Appendix A shows that the output tax will induce more carbon intensity reduction, compared to the Pigouvian tax.

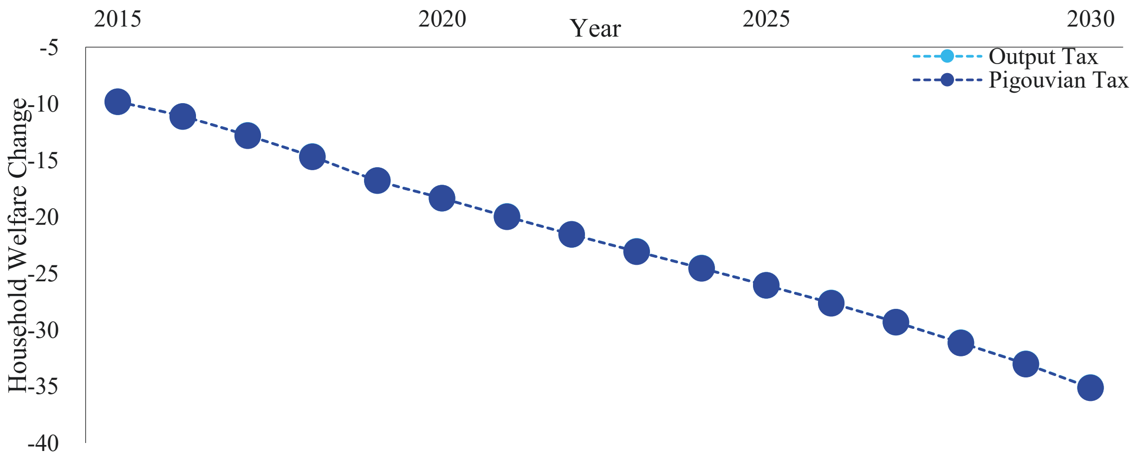


Fig. 1.10 The Household Welfare Change under the Output and Pigouvian Tax (Unit: 10^{12} CNY)

Fig. 1.10 shows how the output and Pigouvian tax will affect the household welfare over time. Both taxes will decrease the household welfare, and this policy effect will be strengthened as the time goes by. According to Fig. 1.10, there are almost no differences in this policy effect between the two taxes. This result implies that the output and Pigouvian tax have equal welfare effects. Similarly, Fig. A1.6 in Appendix A shows the policy effect on the RGDP. Both taxes will decrease the RGDP, and the policy differences between the two taxes are also minimal.

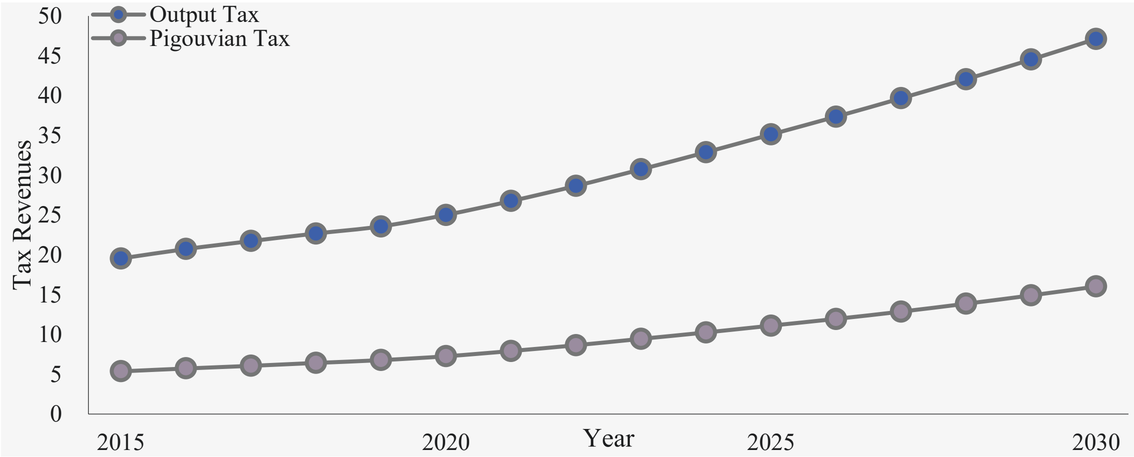


Fig. 1.11 The Tax Revenues under the Output and Pigouvian Tax (Unit: 10^9 CNY)

Fig. 1.11 shows the comparison of the tax revenues generated in the 1% output and Pigouvian tax. According to Fig. 1.11, the tax revenues under the output tax will be more than four times that under the Pigouvian tax, implying that the output tax is more conducive to the implementation of complementary polices, such as the recycling of the tax revenues.

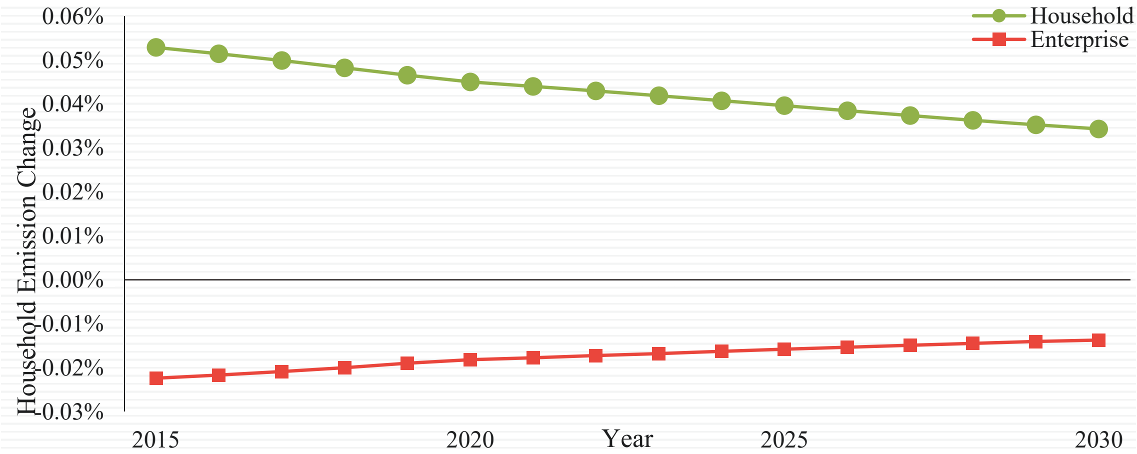


Fig. 1.12 The Household Emission Change under Recycling the Tax Revenues

Fig. 1.12 shows the household emission change under the revenues recycled to the household and enterprise compared to the revenues kept in the governmental budget (government policy). According to Fig. 1.12, the household receiving the revenues (household policy) will induce the biggest household emissions. This is because the household income will be the highest in the household policy. Under recycling the tax revenues, the government or enterprise only partially gives their increasing income to the household through the money transfer. The economic intuition underneath Fig. 1.12 is that the household emissions are positively related to the income.

Fig. A1.7 in Appendix A shows the relative change of the total emissions under the revenues recycled to the household and enterprise in comparison with the government policy. Recycling the revenues to the enterprise (enterprise policy) will induce the highest total emissions, while the government policy will induce the lowest total emissions, implying that the government policy is the most environmentally friendly way to use the tax revenues. Similarly, Fig. A1.8 in Appendix A shows the carbon intensity change in the household and enterprise policy compared to the government policy. The enterprise policy will induce the highest carbon intensity, and thus this policy is the least environmentally friendly.

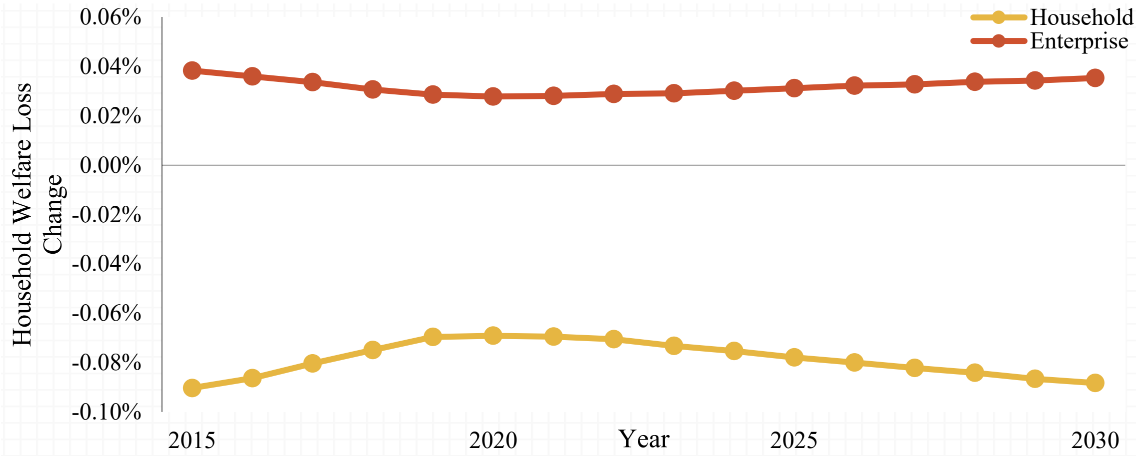


Fig. 1.13 The Change of the Household Welfare Loss under Recycling the Tax Revenues

Fig. 1.13 shows the change of the household welfare loss in the household and enterprise policy compared to the government policy. The household will have the largest welfare in the household policy, but this policy will still induce the net welfare loss. This finding implies that the tax revenues cannot cover the household welfare loss owing to the carbon tax. The household will suffer more welfare loss in the enterprise policy than that in the government policy, implying that the enterprise gives a smaller proportion of its income as the money transfer to the household compared to the government. The finding in Fig. 1.12 corresponds to the microeconomic theory that market mechanism allocates resources more efficiently than governmental intervention. Fig. A1.9 in Appendix A shows the RGDP loss in the household and enterprise policy relative to the government policy. Recycling the revenues to the government will incur the lowest amount of the RGDP loss.

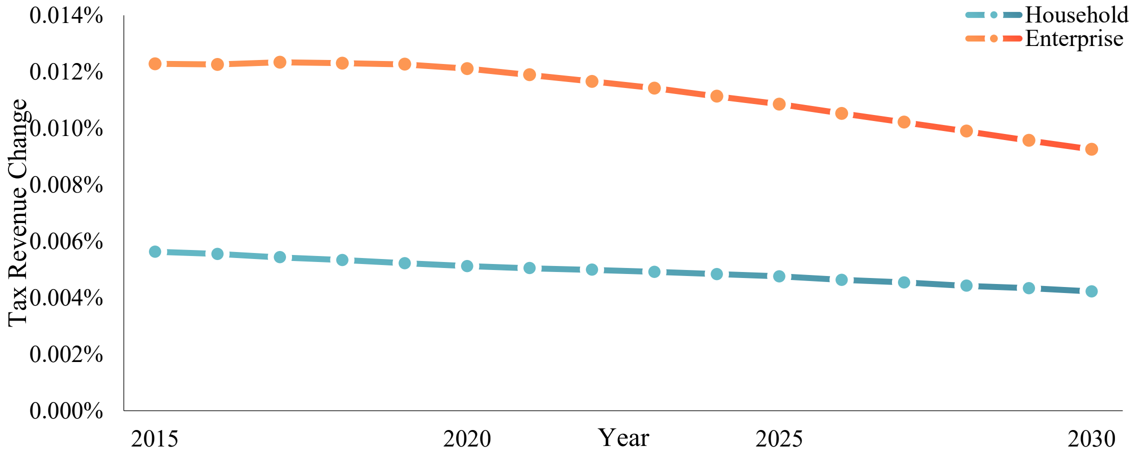


Fig. 1.14 The Tax Revenue Change under Recycling the Tax Revenues

Fig. 1.14 shows the change of the tax revenues in the household and enterprise policy compared to the government policy. Recycling the revenues to the enterprise will induce the highest amount of the tax revenues, which implies that the government will intervene the market mechanism the most in the enterprise policy. This finding complies with the economic intuition that more governmental intervention induces lower efficient allocation of resources and thus more deadweight loss.

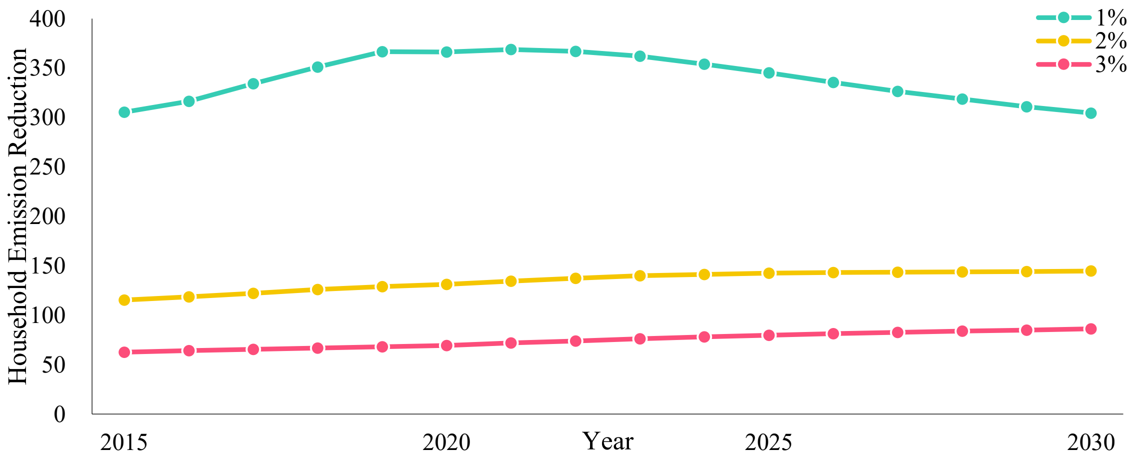


Fig. 1.15 The Marginal Policy Effect on the Household Emission Reduction (Unit: 10^6 t)

Fig. 1.15 shows the marginal policy effect of the carbon tax on the reduction of the household emissions. According to Fig. 1.15, this marginal effect will decrease as the tax rate increases; generally, the effect of the 2% and 3% tax is approximately 1/3 and 1/6 that of the 1% tax respectively. The effect of the 1% tax increased during 2015–2019 but will decrease during 2020–2030. By comparison, the effect of the 2% and 3% tax will slightly increase over the research period. This decreasing marginal policy effect implies that a carbon tax may be not enough to achieve more ambitious mitigation targets. Fig. A1.10 in Appendix A shows that the marginal effect on the total emissions is quite similar to the marginal effect on the household emissions.

Fig. A1.11 in Appendix A shows the marginal effect on the carbon intensity, which differs from the marginal effect on the carbon emissions. Although the 1% tax will still have the biggest marginal effect, the policy differences varying across the tax rates will be much smaller than that of the carbon emissions. According to Fig. A1.11, this marginal effect will decrease over time, and all the three curves will have an identical trend.

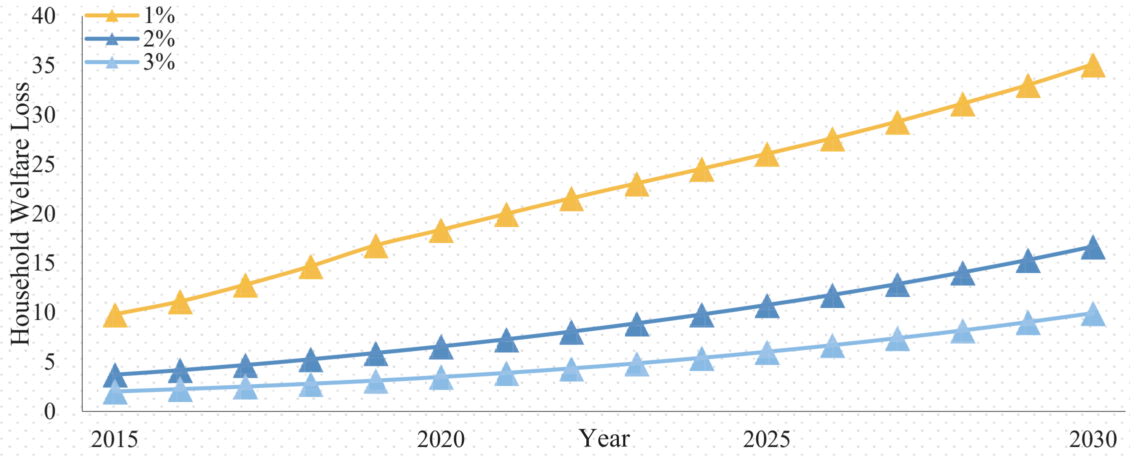


Fig. 1.16 The Marginal Policy Effect on the Household Welfare Loss (Unit: 10^{12} CNY)

Fig. 1.16 shows the marginal effect of the carbon tax on the household welfare loss. This marginal effect will decrease as the tax rate increases, but it will be strengthened over time. The effect of the 2% and 3% tax is about 1/3 to 1/2 and 1/6 to 1/4 that of the 1% tax respectively. Similarly, Fig. A1.12 in Appendix A shows that the diminishing marginal effect on the RGDP loss will increase as the time goes by. In 2015–2019, the effect of the 1% tax increased at a higher rate, but the increase rate will be much lower in 2020–2030. By comparison, the effect of the 2% and 3% tax will steadily increase over time.

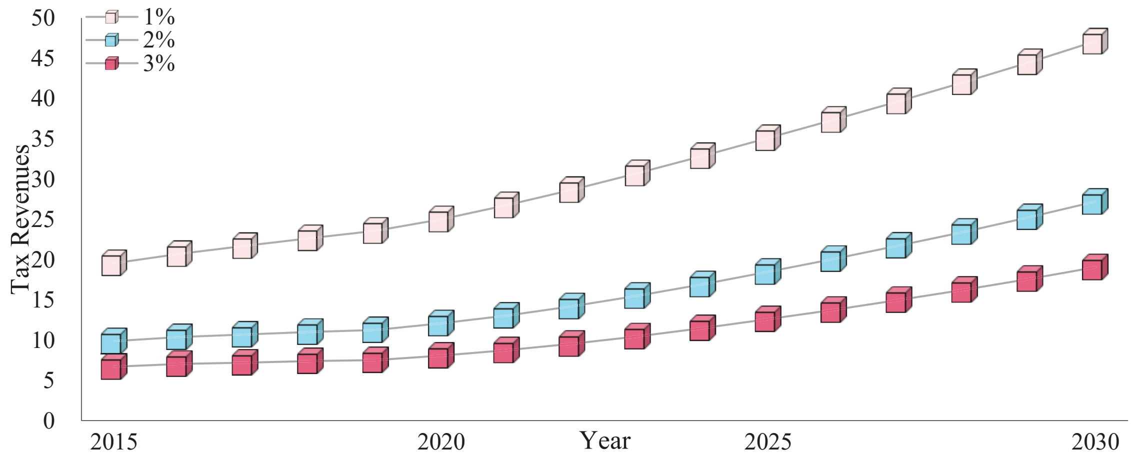
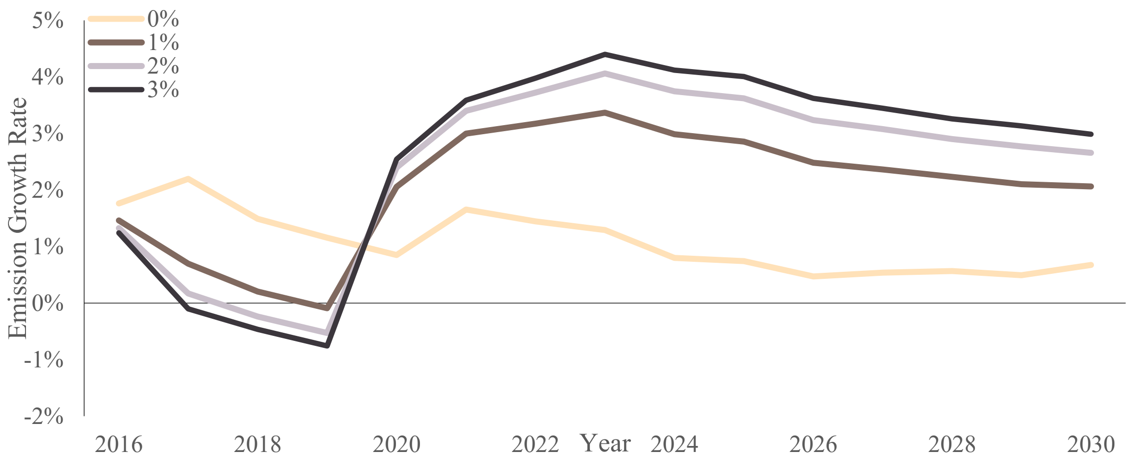


Fig. 1.17 The Marginal Policy Effect on the Tax Revenues (Unit: 10^9 CNY)

Fig. 1.17 shows the marginal policy effect of the carbon tax on the tax revenues over the studied period. According to Fig. 1.17, the diminishing marginal effect on the revenues increased at a relatively lower rate before 2019 and will increase much faster since 2020. Hence, the diminishing marginal effect on the revenues is analogous to the microeconomic theory of diminishing marginal utility.



Note: 0% refers to the baseline scenario.

Fig. 1.18 The Emission Growth Rate in the Baseline and Tax Scenarios

Fig. 1.18 shows the projected emission growth rate over the studied period. In all the scenarios, the projected emission growth rate in 2030 will not approach zero or become negative. This result implies that China's INDC target of peaking its emissions in 2030 will not be met if the carbon tax is the only climate policy that has been implemented. Fig. A1.7 in Appendix A shows that recycling the revenues to the household or enterprise will only slightly change the total emissions, compared to the revenues kept in the governmental budget. Hence, implementing the revenue recycling policy as the complementary policy of the carbon tax will still not help China meet this INDC target.

The carbon intensity in 2005 is calculated as 0.31 kg/CNY, whilst the carbon intensity in 2030 will be 0.074 kg/CNY in the baseline scenario. As the projected intensity in 2030 will be lower than 65% of the 2005 level, China can meet its INDC target of the carbon intensity reduction even if no tax is imposed. Fig. A1.11 in Appendix A shows that the tax will slightly decrease the carbon intensity over time, implying that the INDC target of the intensity reduction will be also met in the tax scenarios.

Results of the Sensitivity Analysis

Table 1.3 The Comparisons of the Model Results in 2015

Variables	50%	20%	10%	-10%	-20%	-50%
Household Emissions	-14.00%	-6.27%	-3.27%	3.57%	7.48%	21.92%
Total Emissions	-14.12%	-6.33%	-3.30%	3.60%	7.55%	22.13%
Carbon Intensity	-0.087%	-0.035%	-0.017%	0.017%	0.035%	0.088%
Welfare Loss	23.90%	10.71%	5.58%	-6.09%	-12.78%	-37.43%
Tax Revenues	-15.07%	-6.74%	-3.51%	3.83%	8.03%	23.51%
RGDP Loss	23.82%	10.68%	5.56%	-6.08%	-12.75%	-37.35%

Table 1.4 The Comparisons of the Model Results in 2030

Variables	50%	20%	10%	-10%	-20%	-50%
Household Emissions	-10.71%	-4.68%	-2.41%	2.58%	5.34%	14.95%
Total Emissions	-10.84%	-4.73%	-2.44%	2.61%	5.40%	15.12%
Carbon Intensity	-0.10%	-0.041%	-0.020%	0.020%	0.041%	0.10%
Welfare Loss	27.57%	12.04%	6.21%	-6.63%	-13.73%	-38.46%
Tax Revenues	-11.78%	-5.14%	-2.65%	2.83%	5.85%	16.37%
RGDP Loss	27.50%	12.01%	6.20%	-6.62%	-13.71%	-38.40%

Table 1.3 and 1.4 show the results of the sensitivity analysis. If the economy becomes more inflexible, both the carbon emissions and intensity will increase. This is because in a less flexible economic, shifting to the low-carbon economy is more costly because of the high transaction costs. In contrast, the economic flexibility is negatively related to the household welfare loss and RGDP loss. This is because the mitigation costs would be lower in less flexible economies than that in more flexible economies (de La Grandville 1989). Similarly, Lu and Stern (2016) explored how the elasticity parameters affected the costs of the carbon tax in a CGE model, concluding that less flexible economies would induce the lower GDP loss under the carbon tax, and more flexible economies would have higher costs.

Over the research period 2015–2030, the impacts of the elasticity parameters on the carbon emissions and tax revenues will increase, whilst the impacts on the other indexes will decrease. Generally, the percentage changes of the major indexes of the CGE model are much smaller than the corresponding percentage changes of the elasticity parameters, implying that the results of the CGE model are robust to the uncertainties of the elasticity parameters.

Table 1.5 The LMDI Decomposition of the RGDP Change in 2015 and 2030

Year	Parameter Change	RGDP ($\Delta g_k/g_d$)	Emission Abatement ($\Delta A_k/g_d$)	Mitigation Cost ($\Delta C_k/g_d$)	Baseline Intensity ($\Delta I_k/g_d$)
2015	50%	23.82%	23.68%	0.14%	0
	20%	10.68%	10.61%	0.068%	0
	10%	5.56%	5.53%	0.037%	0
	-10%	-6.08%	-6.03%	-0.043%	0
	-20%	-12.75%	-12.65%	-0.093%	0
	-50%	-37.35%	-37.02%	-0.33%	0
2030	50%	27.50%	27.29%	0.21%	0
	20%	12.01%	11.91%	0.10%	0
	10%	6.20%	6.14%	0.054%	0
	-10%	-6.62%	-6.56%	-0.062%	0
	-20%	-13.71%	-13.58%	-0.13%	0
	-50%	-38.40%	-37.94%	-0.46%	0

Table 1.5 shows the LMDI decomposition of the RGDP change resulting from the changes of the elasticity parameters. According to Table 1.5, the relative carbon emission abatement will have a predominant influence on the RGDP change, whilst the average mitigation cost will not make a significant contribution to the RGDP change. The LMDI decomposition in 2015 shows very similar findings to that in 2030. Different from Lu and Stern (2016), the baseline carbon intensity will not correlate with the RGDP change induced by the elasticity parameter changes in this chapter. This is because in the baseline scenario, the RGDP is defined as the sum of the added-values in the Input-Output Table, and the carbon emissions are defined as the energy consumption, according to China Energy Statistical Yearbook (NBS 2016), multiplied by the carbon emission factors, given by IPCC

(2006). Therefore, defined as the carbon emissions divided by the RGDP, the carbon intensity will remain unchanged over time irrespective of the elasticity parameter changes in the baseline scenario.

Discussion

The CGE results in this chapter empirically shows that the carbon tax will decrease the carbon emissions significantly. This finding is in line with Dong, Dai et al. (2017) who used a 30-Chinese-province CGE model to show that the carbon tax would decrease the Chinese industrial carbon emissions significantly. Similar policy effect could be also found worldwide: for example, the carbon tax would have the great capacity to decrease the greenhouse gas emissions in South Africa (van Heerden, Blignaut et al. 2016); the carbon tax could achieve the primary goal of reducing the carbon emissions in the US (Macaluso, Tuladhar et al. 2018).

Different from the policy effect on the carbon emissions, the effect of the tax on the carbon intensity is not distinct in this chapter. This finding disagrees with the previous research showing that the tax could decrease the carbon intensity by over 20% and 25% in Liaoning Province and the rest of China (ROC) respectively compared to the baseline scenario (Li, Dai et al. 2018). The result difference lies in the structure of the CGE model: Li, Dai et al. (2018) modelled the provincial inflow and outflow of the consumption and production if the tax rate differed across the regions. In contrast, the carbon tax is imposed at the same rate across China with the rest of the world (RW) implicitly included in this chapter. Also, there existed a scale effect of the production and consumption in Liaoning Province compared to the ROC in Li, Dai et al. (2018), whilst the economic scale of the RW is assumed to be not affected by the Chinese carbon tax in this chapter.

The carbon tax will decrease the household welfare over the research period. This finding abides by Guo, Zhang et al. (2014) who used a CGE model to investigate the socioeconomic impacts of the Chinese carbon tax and empirically found that the policy effect of the Chinese carbon tax on the welfare was negative. Previous studies with similar findings were also performed elsewhere: for example, Orlov and Aaheim (2017) used a multi-regional and multi-sectoral CGE model to empirically show that the international climate policy could decrease the private welfare by 1.8% in Russia; Woollacott (2018) used the forward-looking dynamic CGE model to show that the marginal net welfare cost of the US carbon tax was 27 \$/t CO_2.

The carbon tax will induce the deadweight loss of the real GDP (RGDP) over the research period. This finding complies with Dong, Dai et al. (2017) who used a 30-Chinese-province CGE model and concluded that the implementation of the carbon tax would impede the economic development for all the Chinese provinces. Similarly, Zhang, Guo et al. (2016) applied a CGE model to investigate the policy effects of the Chinese carbon tax at the provincial level and empirically found that the carbon tax could result in a slowdown in the Chinese economic growth. Similar empirical evidence could be found worldwide: for example, the CGE results implied that the application of the carbon tax led to the adverse effects on the GDP in Finland (Khastar, Aslani et al. 2020); there was an inversely proportional relationship between the carbon tax level and GDP in Brazil (Grottera, Pereira et al. 2017).

The marginal effects of the carbon tax on the emission reduction will decrease as the tax rate increases. This finding agrees with the previous research showing that the carbon tax had a decreasing marginal impact on the total emission reduction, implied by the non-equilibrium bottom-up model (Knobloch, Pollitt et al. 2019). Similarly, Jorgenson, Goettle et al. (2018) employed an intertemporal general equilibrium model and empirically found that the emission abatement increased at a decreasing rate with the increasing severity of the carbon taxation.

The carbon tax will have a decreasing marginal effect on the RGDP in this chapter. This finding fits in with Xiao, Niu et al. (2015) who used a dynamic recursive multi-sectoral CGE model to empirically show that the higher tax rate could cause more negative effects on the GDP, but the carbon tax had a decreasing effect with the increase of the tax rate. Similarly, Mardones and Lipski (2020) used a CGE model to show that the negative effect of the carbon tax on the agricultural output in Chile would decrease as the tax rate increased.

The revenue recycling policy in this chapter will have a minimal impact on the CGE model equilibrium over the studied period. This finding disagrees with Sands (2018) who used a CGE model to empirically show that the revenue recycling could make a difference to the policy effects of the carbon tax in the US. The result difference between Sands (2018) and this chapter lies in the way the revenues are recycled: the revenues were recycled as the reduction in the labour or capital tax in Sands (2018). By comparison, in this chapter, the labour or capital tax is exogenously given in 2015 China Input-Output Table, and thus the tax revenues are recycled as the increase in the income of the targeted entity directly.

Hence, the designed revenue recycling policy could be one major limitation in this chapter. This is because how the recycling policy stimulates the economic growth is not fully explored in this chapter. Future research may lie in the detailed study of the mechanism that the revenue recycling complements the policy effects of the carbon tax.

Another limitation in this chapter is that I have not considered the potential benefits of the carbon tax in addition to the emission reduction. Overlooking the benefits is likely to induce a biased evaluation of the carbon tax, and thus a climate policy is usually not appealing to the government. If all the benefits had been considered, the carbon tax might have increased the GDP and welfare. Therefore, I will explore the potential benefits of the carbon tax in the next chapters where the benefits are endogenously determined in the CGE framework.

The simulated 1%, 2%, and 3% tax cannot help China meet the INDC target of peaking the emissions in 2030. To meet this INDC target, China needs to implement more climate policies. The highest amount of the tax rate, in this chapter, will be 9.8 $\$/t\ CO_2$ in 2030 at the 3% tax, but it is much lower than the designed carbon price of 20–120 $\$/t\ CO_2$ in Dong, Dai et al. (2017). According to Yang, Teng et al. (2018), the marginal abatement cost to achieve China's INDC target was equivalent to 13.2 $\$/t\ CO_2$. Hence, under a carbon tax with a much higher tax rate, China could meet the INDC target of peaking its emissions.

Policy Implications

The carbon tax should be imposed on the consumption of the electricity as the electricity in China is mainly generated from nonrenewable energy. A differentiated carbon tax on the electricity subsectors is better than a uniformed tax on the electricity sector, because the electricity subsectors exploiting renewables should not be taxed. Although the differences of the policy effects between the output tax and Pigouvian tax are minimal, the output tax is more advantageous to be implemented as a second-best climate policy. Recycling the tax revenues is not an important complementary policy of the carbon tax because it minimally changes the policy effects of the carbon tax. The tax has diminishing marginal effects both on the emission reduction and welfare loss. The carbon tax cannot help China meet the INDC target of peaking the emissions; a carbon tax with a higher tax may help China meet this INDC target.

Conclusion

Modelling the electricity carbon emissions from the electricity consumption perspective is beneficial to revealing the genuine household and sectoral emissions as the electricity generation in China is not environmentally friendly. Disaggregating the electricity sector is helpful to implement the carbon tax fairly as the electricity subsectors exploiting renewables should not be taxed. The disaggregation of the electricity sector will change the policy effects of the carbon tax. Specifically, the electricity disaggregation will increase the carbon emissions by 5% but decrease the welfare loss by less than 2%.

The policy effects of the output tax, imposed on the outputs of the nonrenewable energy sectors, are different from that of the Pigouvian tax, imposed on the consumption of the nonrenewable energies directly. The output tax will induce 1% less household emission reduction but 0.1% more total emission reduction. There are almost no differences in the policy effect on the RGDP and household welfare between the two taxes if the tax is implemented as a first-best climate policy. Nevertheless, the output tax is more advantageous to be implemented as a second-best climate policy, because the tax revenues under the output tax will be more than four times that under the Pigouvian tax. Therefore, the output tax is preferable because the implementation of a first-best policy is usually constrained by socioeconomic factors in the reality.

Recycling the revenues to the government is the most environmentally friendly and economically efficient policy. However, from the household perspective, recycling the tax revenues to the household is more appealing as the welfare loss is the least, but this policy still cannot compensate the household welfare loss resulting from the carbon tax. The household may not support the enterprise policy, but this policy will induce the highest amount of the tax revenues. Nevertheless, there will be less than 0.1% differences in the policy effects of recycling the tax revenues. This result implies that recycling the revenues is not an important complementary policy to the carbon tax.

There are diminishing marginal effects of the carbon tax on the carbon emissions, carbon intensity, household welfare, tax revenues, and RGDP loss. However, the diminishing marginal effects will vary across the indexes: the marginal effect of the 2% and 3% tax on the emissions is approximately 1⁄3 and 1⁄6 that of the 1% tax respectively; The marginal effect of the 2% and 3% tax on the household welfare loss is about $1/3$ to $1/2$ and $1/6$ to $1/4$ that of the 1% tax respectively. All the marginal effects will increase over the research period except that the marginal effect of the 1% tax on the carbon emissions will fluctuate over time.

The carbon tax alone cannot help China meet the INDC target of peaking the emissions in 2030 even if the revenue recycling is implemented as the complementary policy of the tax. Nevertheless, China can meet its INDC target of the carbon intensity reduction in 2030 even if no tax is imposed. As the carbon tax slightly reduces the carbon intensity over time, this INDC target will be also met in the tax scenarios.

The carbon tax will induce less welfare loss as well as less emission reduction if the Chinese economy becomes more inflexible. The LMDI decomposition analysis shows that the RGDP changes resulting from the elasticity parameter changes are mainly influenced by the changes of the relative emission abatement but irrelevant to the changes of the baseline carbon intensity. As the percentage changes of the major indexes are much smaller than the corresponding percentage changes of the elasticity parameters, I conclude that the CGE model is not severely influenced by the elasticity parameters.

Chapter 2: The Ancillary Benefit of the Carbon Tax

Introduction

Although a climate policy is mainly targeted to curb carbon emissions, it may also improve air quality because combustion of fossil fuels generates not only greenhouse gases but also other hazardous pollutants" (Cushing, Blaustein-Rejto et al. 2018). In other words, carbon emissions and air pollutant emissions often originate from the same stationary and mobile sources (Workman, Blashki et al. 2019). Hence, a climate policy which curbs carbon emissions is likely to reduce air pollutant emissions, too. Such kinds of benefits are called ancillary benefits, also known as secondary benefits, co-benefits or spill-over benefits in the literature (Longo, Hoyos et al. 2012). The ancillary benefits of a climate policy usually include improvements in human health and life expectancy, reduced materials and crop damage, better visibility, reduced road traffic congestion, and a diminished solid waste load (Dessus and O'Connor 2003). In contrast, primary benefits of a climate policy include "the direct benefits of greenhouse gas mitigation through avoided climatic change and the reduced likelihood of any ensuing net adverse impacts" (Corfee-Morlot and Agrawala 2004). Ancillary benefits stem from a climate policy but are different from the policy's primary aim of climate protection (Rubbelke 2006). Pearce (2000) empirically found that a climate policy's ancillary benefits could be comparable in size to its primary benefits targeted at the climate change.

Despite their significant socioeconomic impacts, the ancillary benefits of a climate policy are usually overlooked within the framework of a CGE model. For example, Dong, Dai et al. (2017) designed a 30-Chinese-province CGE model to analyse the policy effects of the carbon tax, concluding that the tax would induce GDP loss. Overlooking the ancillary benefits corresponds to the fact that previous researchers tend to focus on the economy-wide effects of climate policies only (Orlov and Aaheim 2017) but neglect the important linkage between economic activities and environmental problems including air pollution (Aunan, Berntsen et al. 2007). This is because the clean air belongs to the domain of public goods, and there usually exist difficulties in internalising the externalities.

Conversely, accounting for the ancillary benefits is likely to increase the attractiveness of a climate policy for governmental implementation. For example, if ancillary benefits are considered, the general public's willingness to pay for climate policies were estimated to be 53–73% higher, implied by the Contingent Valuation Method (Longo, Hoyos et al. 2012). Similarly, Dessus and O'Connor (2003) used a CGE model, empirically showing that Chile could reduce its carbon emissions by almost 20% from the 2010 baseline with no net welfare loss if the ancillary benefits were considered.

When analysing the ancillary benefits of a climate policy, researchers tend to use a partial equilibrium model. For example, Yang, Teng et al. (2018) used cost-benefit analysis (CBA) to evaluate the policy effects of a Chinese carbon tax, showing that in the normal end-of-pipe control (NEPC) scenario, the carbon mitigation cost was 0.08% of the GDP loss, compensated by the environmental benefits accounting for 0.14% of the GDP. The CBA method in Yang, Teng et al. (2018) neglected the existence of feedback loops in their research framework. For example, the carbon tax will reduce the carbon emissions, which in turn will increase the labour health and thus labour input. The increase of the labour input will promote the GDP growth, which will increase the energy consumption and thus carbon emissions. Finally, the emission reduction effect of the carbon tax will be impaired in the balancing loop. Hence, if all the socioeconomic and environmental feedbacks had been analysed using a general equilibrium model, the results could have been different from that in Yang, Teng et al. (2018).

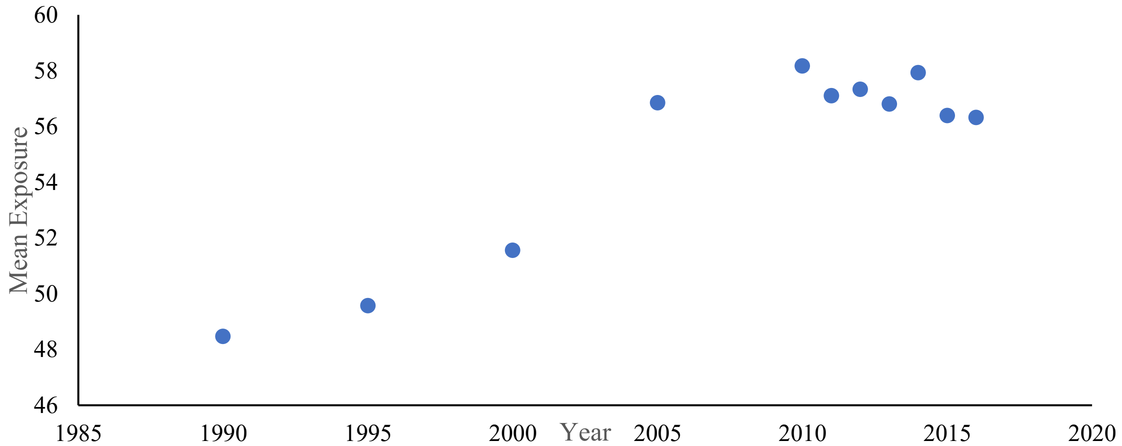
Health benefits account for approximately 70–90% of the total ancillary benefits of a climate policy (Ostblom and Samakovlis 2007), and thus they could be considered as the representation of the ancillary benefits. In other words, this chapter focuses on the health benefit that is linked to the reduction of the air pollutant concentrations. In the China example, fine particulate matter with a diameter of 2.5 microns or less ($PM_{2.5}$) is usually used to denote the air quality, because this air pollutant severely affects the labour productivity (Zhang and Jin 2017, Li, Zou et al. 2020). The exposure to $PM_{2.5}$ can cause lung and respiratory diseases, increase plaque formation in the blood vessels, affect the autonomous nervous system, and trigger premature deaths (He, Xue et al. 2012, Liu, Li et al. 2014). "In a fine particle ($PM_{2.5}$) ranking of Global Burden of Disease regions, East Asia came out on top, both for its mean level in 2001–2010 estimated at 50 $\mu g/m^3$ and for its trend at +1.6 $\mu g/m^3/year$" (He, Liu et al. 2019). Therefore, $PM_{2.5}$ has recently become a primary pollutant which threats the health of the Chinese population (Liu, Li et al. 2014).

Although $PM_{2.5}$ does affect human health and thus equilibrium conditions, little research has been comprehensively conducted to model the health impact of a climate policy in the literature. Although Xu, Xu et al. (2018) used a dynamic CGE model to evaluate the impact of a coal resource tax on the carbon reduction and haze, a more general and broader climate policy is needed to cope with the climate issue as well as the air pollution, considering that oil and gas are becoming more and more important in China's energy budget currently. On the contrary, Hu, Sun et al. (2019) and Wei, Li et al. (2018) only evaluated the policy effects of controlling the air pollution, but they neglected the potential effects of the policy on the reduction of the greenhouse gases. Aunan, Berntsen et al. (2007) employed a CGE model to assess the costs and benefits of the climate commitment, concluding that China can reduce its emissions without suffering welfare loss. However, Aunan, Berntsen et al. (2007) emphasised that half of the benefits originated from the agricultural yields using 1997 input–output data. According to 2016 China Statistical Yearbook (NBS 2016), the agricultural output occupied 17.9% of the Chinese GDP in 1997, but the share decreased to 8.9% in 2015. Hence, the proportion of the agricultural ancillary benefits may be much less in 2015–2030 than that in 1997. Therefore, the CGE results presented in the aforementioned studies tend to evaluate the ancillary benefits of a climate policy biasedly.

This chapter contributes to the literature by using the CGE model to comprehensively model the ancillary (health) benefit as well as the other policy effects of the carbon tax. Specifically, the imposition of the carbon tax will decrease the fossil fuel combustions, leading to the reduction of the CO_2 and $PM_{2.5}$ emissions. The decreasing $PM_{2.5}$ emissions will cause the reduction in its concentrations. Hence, the ancillary benefit is modelled as the improvement in the labour health and thus the increase in the productivity originating from the reduction of the $PM_{2.5}$ concentrations. In summary, accounting for the ancillary benefit may increase the labour productivity and thus boost the economic growth, which could decrease the welfare loss resulting from the carbon tax.

Method

The model employed in this chapter is based on the electricity model (output tax) defined in the previous chapter. However, I have quantified the health benefit in the environmental block of the CGE model in this chapter. To begin with, I have obtained the mean $PM_{2.5}$ exposure data from the World Bank shown in Fig. 2.1.



Data Source: World Development Indicators by World Bank (WB)

Fig. 2.1 The $PM_{2.5}$ Mean Exposure ($\mu g/m^3$) in China

Fig. 2.1 shows the historical mean $PM_{2.5}$ exposure in China. According to Fig. 2.1, the exposure increased dramatically in 1990–2010 and fluctuated in 2010–2016. If China implemented strict climate policies to control the combustion of fossil fuels, the $PM_{2.5}$ concentrations would decrease in the future (Wang, Zhao et al. 2017). Unlike carbon dioxide, $PM_{2.5}$ does not have universally acknowledged emission factor data published by IPCC. If the emission factor of $PM_{2.5}$ remains unchanged, the $PM_{2.5}$ emissions are proportional to the consumption of the fossil fuels.

Previously, the projected $PM_{2.5}$ emissions in China tend to fluctuate dramatically owing to the various projection models applied or influential factors considered. The results of some previous research are compiled in Table 2.1.

Table 2.1 Projected $PM_{2.5}$ Emission Change in China

Authors	Research Period	Changes of $PM_{2.5}$ emissions
Amann, Kejun et al. (2008)	2005–2030	-10%
Cofala, Bertok et al. (2012)	2010–2030	-20%
Wang, Zhao et al. (2014)	2010–2030	-8%
IEA (2017)	2017–2040	-50%
Cai, Ma et al. (2018)	2013–2030	Slightly (Unspecified)

Table 2.1 summarises the projected changes of the Chinese $PM_{2.5}$ emissions in some previous studies. The projected change in IEA (2017) is much larger than that in the other studies because the projection in IEA (2017) was based on the new-policies scenario. Based on World Energy Outlook 2012, the data in Cofala, Bertok et al. (2012) could be outdated as World Energy Outlook is published annually. Cai, Ma et al. (2018) used the chemical transport model (GEOS-Chem) to investigate the effects of the air pollutant control policies in China, but they only mentioned the slight decrease of the $PM_{2.5}$ emissions without any exact data under the current legislation and implementation status. Amann, Kejun et al. (2008) and Wang, Zhao et al. (2014) showed quite similar projected changes of the baseline $PM_{2.5}$ emissions. Considering the overlapping of the research period as well as the citation frequency, I have used the baseline $PM_{2.5}$ emission data in Wang, Zhao et al. (2014) who argued that the $PM_{2.5}$ emissions in China were 11.786 Mt in 2010 and would be 11.736 Mt in 2020 and 10.872 Mt in 2030. In this chapter, the $PM_{2.5}$ emissions were estimated as 11.761 Mt in 2015 on the assumption that the $PM_{2.5}$ emissions would change at a constant rate during 2010–2020 and 2021–2030. The projected $PM_{2.5}$ emissions are shown in Fig. 2.2.

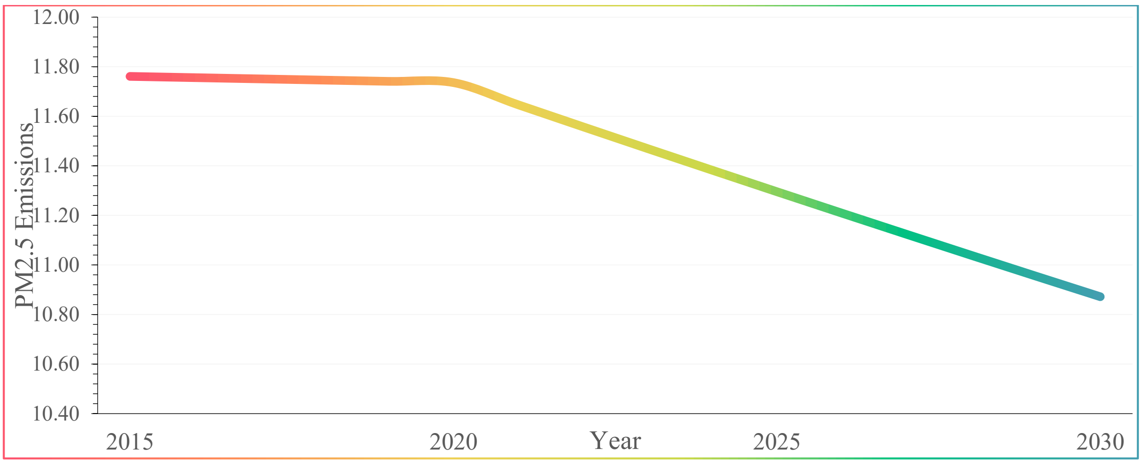


Fig. 2.2 The Projected $PM_{2.5}$ Emissions in the Baseline Scenario (Unit: Mt)

Fig. 2.2 shows the projected $PM_{2.5}$ Emissions in the baseline scenario of this chapter. According to Fig. 2.2, the $PM_{2.5}$ Emissions decreased slightly in 2015–2020 and will decrease dramatically in 2021–2030. This dramatic emission decrease in the future 10 years corresponds to the Chinese government's efforts to control the severe air pollution (He, Zhang et al. 2020).

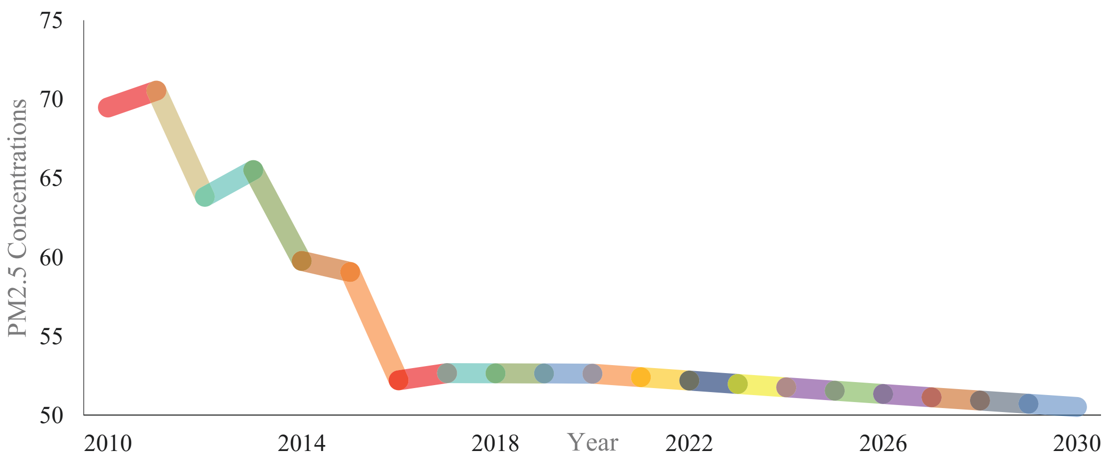
According to Zhang, Cai et al. (2017), the average contribution rate of the primary source, namely the anthropogenic activities (consisting of the vehicle exhaust, coal combustion, dust, biomass burning, and industrial emissions), to the $PM_{2.5}$ concentrations is 60% and 50% in the northern and southern

China respectively. By comparison, the other source, consisting of the secondary source (formed through processes in the atmosphere) and the $PM_{2.5}$ emissions from the rest of the world, accounts for 40% and 50% of the $PM_{2.5}$ concentrations in the northern and southern China respectively. According to Central People's Government of the People's Republic of China (CPGPRC), northern and southern China occupy approximately 20% and 25% of the total land in the country (the rest of the country is sparsely populated). Hence, the weighted contribution of the primary source to the $PM_{2.5}$ concentrations is calculated as 54.44%, and the other source accounts for 45.56% of the $PM_{2.5}$ concentrations in China. The impacts of the $PM_{2.5}$ concentrations on the labour productivity are also decomposed into the primary source impact and the other source impact.

The World Bank (WB) data show that the $PM_{2.5}$ concentrations in China fluctuated from 69.48 $\mu g/m^3$ in 2010 to 59.06 $\mu g/m^3$ in 2015, decreased to 52.21 $\mu g/m^3$ in 2016, and remained relatively stable at 52.66 $\mu g/m^3$ in 2017. In this chapter, the projected $PM_{2.5}$ concentrations in 2018–2030 are based on the 2017 data. Over this period, the projected $PM_{2.5}$ concentrations from the other source are assumed to equal $52.66 \times 45.56\% = 23.99$ $\mu g/m^3$, while the projected $PM_{2.5}$ concentrations from the primary source are assumed to vary proportionally to the changes of the $PM_{2.5}$ emissions from the 2017 data, shown in Eq. (2.1).

$$PMC_t = 52.66 \times 45.56\% + 52.66 \times 54.44\% \times \frac{PME_t}{PME_{2017}} \ (t > 2017) \qquad (2.1)$$

Eq. (2.1) shows the projected $PM_{2.5}$ concentrations in 2018–2030. PMC_t denotes the projected $PM_{2.5}$ concentrations in Year t; PME_t is the $PM_{2.5}$ emissions in Year t; PME_{2017} is the $PM_{2.5}$ emissions in 2017. Hence, the baseline $PM_{2.5}$ concentrations in 2010–2030 are shown in Fig. 2.3.



Note: 2010–2017 data from the World Bank; 2018–2030 data projected in this chapter

Fig. 2.3 The Projected $PM_{2.5}$ Concentrations in the Baseline Scenario (Unit: $\mu g/m^3$)

According to Fig. 2.3, the $PM_{2.5}$ concentrations decreased by approximately 11% in 2015–2016, remained stable in 2017–2020, and will steadily decrease since then. In the literature, Cai, Ma et al. (2018) showed that the baseline $PM_{2.5}$ concentrations decreased by 2.1% in 2017–2020, less than the 4.07% decrease in the same period of this chapter. This is because the projection in Cai, Ma et al. (2018)

was based on the legislation in 2012, whilst the projection in this chapter is based on the legislation in 2015. As the legislation is stricter in 2015 than that in 2012, there will be more projected emission reduction in this chapter.

Previous researchers have already studied how the $PM_{2.5}$ concentrations affected the labour productivity. For example, He, Liu et al. (2019) empirically found that a sizable 10 $\mu g/m^3$ increase of the $PM_{2.5}$ concentrations during the entire 3–4 week-period would lead to a 0.5 to 1 percent shortfall in a worker's output. As He, Liu et al. (2019) conducted their research only at the two Chinese manufacturing sites, their research might not comprehensively reflect the average impacts of the $PM_{2.5}$ pollution on the labour productivity in China. In contrast, Zhang and Jin (2017) used the data from China Employer-Employee Survey (CEES), which covers 26 cities, 1121 enterprises, and 10975 employees. Hence, the results of Zhang and Jin (2017) could be much closer to the reality in China. In this chapter, I have referred to Zhang and Jin (2017) who showed that if the $PM_{2.5}$ concentrations increase by 1 $\mu g/m^3$, the labour productivity will decrease by 0.14%. The baseline labour productivity rate is calculated using Eq. (2.2), where PML_t is the labour productivity rate.

$$PML_t = 1 - PMC_t \times 0.14\% \tag{2.2}$$

Eq. (2.2) shows PML_t is exogenously determined by the unit change of the labour productivity to the $PM_{2.5}$ pollution (0.14%), according to Zhang and Jin (2017). In this chapter, the projected baseline labour productivity rate is shown in Fig. 2.4.

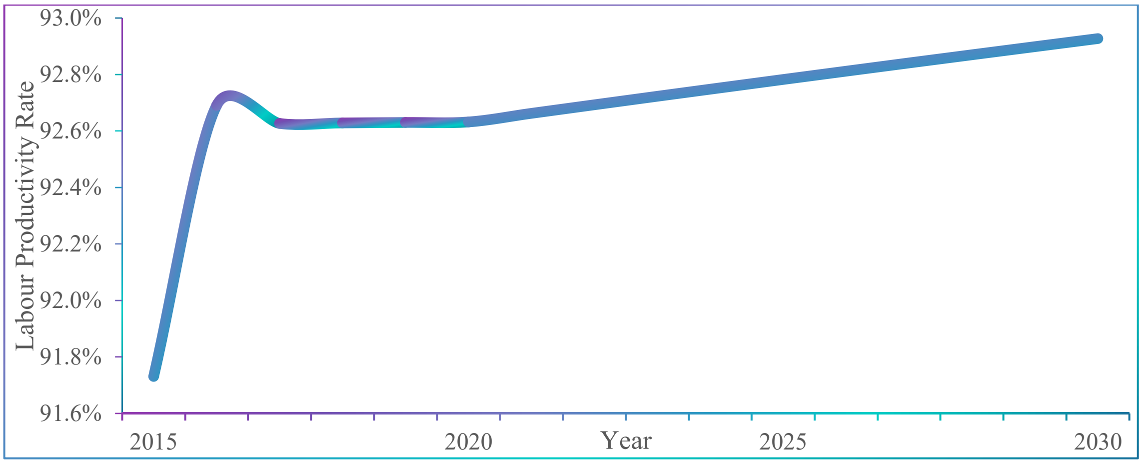


Fig. 2.4 The Labour Productivity Rate in the Baseline Scenario

Fig. 2.4 shows how the labour productivity rate will change over the studied period. The labour productivity rate increased by 1.1% from 2015 to 2016, decreased in 2016–2017, remained stable until 2020, and will steadily increase in 2021–2030. Fig. 2.4 implies that the negative impact of the $PM_{2.5}$ pollution on the baseline labour productivity will decrease since 2017, which complies with the trend of the $PM_{2.5}$ concentrations, shown in Fig. 2.3. Previously, the relationship between the $PM_{2.5}$ pollution and labour productivity has already been confirmed. For instance, Xia, Guan et al. (2016) employed a supply-driven input-output (I-O) model and empirically found that the $PM_{2.5}$ pollution could result in great labour constraints on the supply-side of the economy owing to the $PM_{2.5}$-related diseases. By utilising the piece-wise panel regression methods, Zhang, Hao et al. (2018) also found a significantly negative spatial correlation between the air pollution in nearby areas and the local labour supply. Therefore, I conclude that the labour productivity is negatively related to the $PM_{2.5}$ pollution. In light of this relationship, Eq. (2.3) is defined to show how the simulated carbon tax will affect the labour productivity over time.

$$PML_t = \begin{cases} 1-\left(26.91+32.16\times\frac{TCE_t}{TCE0_t}\right)\times 0.14\% & \text{t} = 2015 \\ 1-\left(23.79+28.43\times\frac{TCE_t}{TCE0_t}\right)\times 0.14\% & \text{t} = 2016 \\ 1-\left(23.99+28.67\times\frac{PME_t}{PME_{2017}}\times\frac{TCE_t}{TCE0_t}\right)\times 0.14\% & \text{t} \geq 2017 \end{cases} \tag{2.3}$$

In Eq. (2.3), TCE_t is the total carbon emissions under the imposition of the carbon tax in Year t; $TCE0_t$ is the baseline total carbon emissions in Year t.

Finally, a sensitivity test is conducted to analyse to what extent the parameter (the unit change of the labour productivity to the $PM_{2.5}$ pollution) will affect the model equilibrium over time. This parameter was derived from the coefficients of the stepwise OLS regressions in Zhang and Jin (2017) whose empirical research was based on the China Employer-Employee Survey (CEES) data. Nevertheless, this parameter was subject to the uncertainties arising from the demographic factors (age, education, and marital status), meteorological factors (temperature, wind, and precipitation), city factors (city scales and location), and enterprise factors (the products). Hence, the sensitivity analysis is necessary to check the impacts of the parametric uncertainties on the model results. In the sensitivity test, the parameter will change by -10%, -5%, -3%, -1%, 1%, 3%, 5%, and 10%. If the corresponding percentage changes of the model results are less than the parametric changes, I will conclude that the model defined in this chapter is robust to the parametric uncertainties; otherwise, remedial meaures need to be taken to cope with the parametric uncertainties.

In this chapter, the ancillary benefit of the carbon tax is represented by the health benefit, which will increase the labour productivity and thus affect the model equilibrium. To analyse the impacts of the health benefit on the carbon emissions and social welfare, I have calculated the result differences between the electricity model, defined in the previous chapter, and the clean-air model, defined in this chapter. The electricity model excludes the health benefit, whilst the clean-air model includes the health benefit.

In the Intended Nationally Determined Contribution (INDC), China has pledged to lower its emissions per unit of the GDP by 60% to 65% from the 2005 level before 2030 (NDRC 2015). The 2005 sectoral carbon intensity is calculated using the sectoral energy consumption data from 2016 China Energy Statistical Yearbook (NBS 2016) and the sectoral output data from 2005 China Input-Output Table (NBS 2005). The 2005 sectoral output has been adjusted by the relative price from 2005 to 2015 according to 2017 China Statistical Yearbook (NBS 2017). In the studied period, the sectoral carbon intensity in the tax scenarios is the same as that in the baseline scenario, because the sectoral energy consumption is assumed to change proportionally to the sectoral output in this chapter.

Model Results

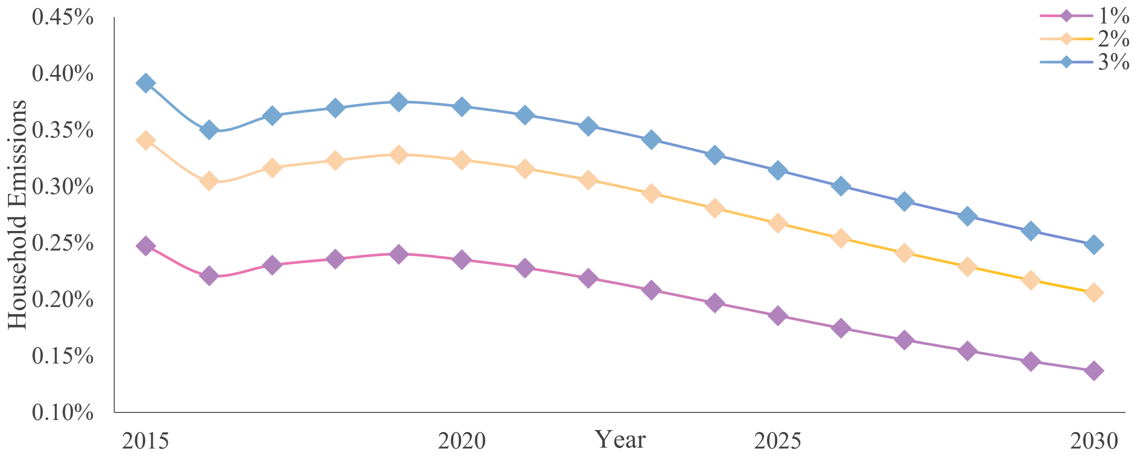


Fig. 2.5 The Health Benefit Impact on the Household Emissions

Fig. 2.5 shows that the health benefit will increase the household emissions in all the tax scenarios. The increase of the tax rate will strengthen the health benefit impact on the household emissions. In the literature, most researchers have agreed that climate policies will give rise to health benefits owing to the reduction of air pollutants, and this evidence can be found internationally (Dessus and O'Connor 2003, Ambasta and Buonocore 2018, Kim, Xie et al. 2020). However, previous researchers tend to neglect that the health benefit could also influence the effects of climate policies in return. The economic intuition underneath Fig. 2.5 is that considering the health benefit will increase the household income, and thus it will increase the household energy consumption and carbon emissions.

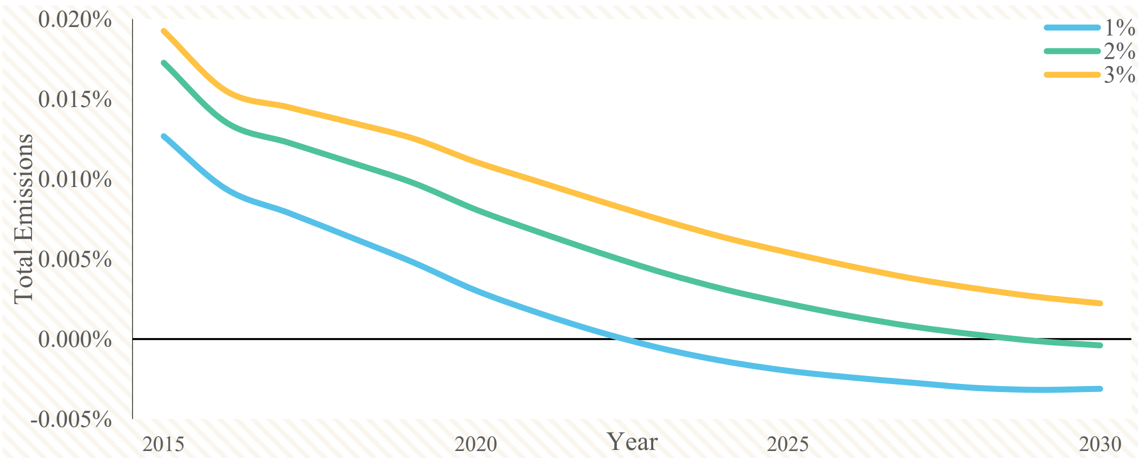


Fig. 2.6 The Health Benefit Impact on the Total Emissions

By comparison, Fig. 2.6 shows that the health benefit will have a smaller impact on the total emissions. This impact will decrease over time, and it will turn negative in 2023 at the 1% tax and in 2028 at the 2% tax. The increase of the tax rate will also strengthen the health impact on the total emissions. This finding agrees with Fox, Zuidema et al. (2019) who reviewed the literature on the public health's role in climate change action, arguing that the health benefit helped underpin the greenhouse gas reduction strategies. However, Workman, Blashki et al. (2018) identified the several constraints, existing in the political economy, which would induce the elusive influence of the health benefit on the development of the ambitious climate policies. In other words, the consideration of the health benefit will reduce the carbon emissions only in the first-best climate policies. As the simulated carbon tax in this chapter is a second-best climate policy, the induced health benefit will not significantly change the policy effect on the carbon emissions.

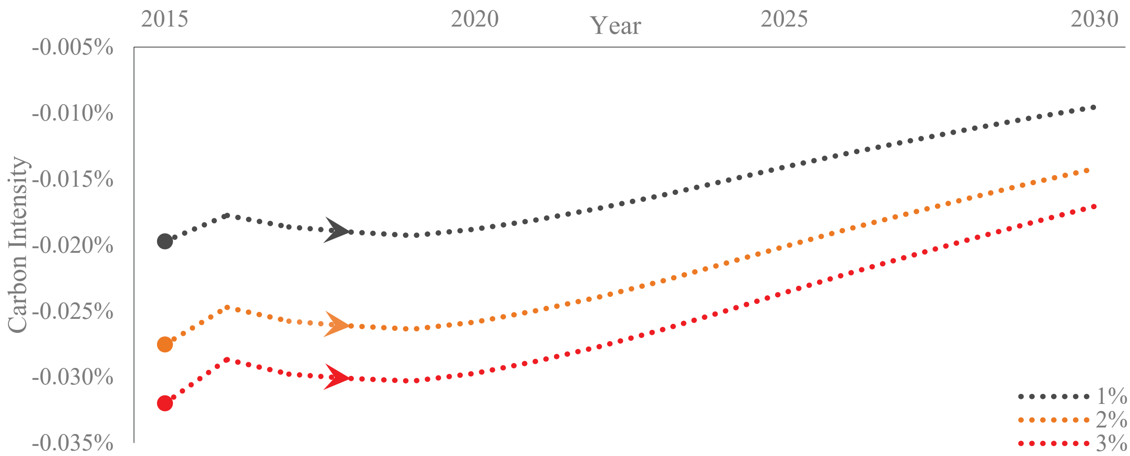


Fig. 2.7 The Health Benefit Impact on the Carbon Intensity

Fig. 2.7 shows that the health benefit will reduce the carbon intensity over time, and this impact will increase as the tax rate rises. In 2015–2020, the health benefit impact fluctuated, and then it will decrease steadily in 2021–2030. In the literature, many studies argued that controlling the air pollution and thus the improved health status would reduce the carbon intensity. For instance, Wang, Ye et al. (2014) developed a multi-region optimisation model to assess the value of a long-term climate policy agenda in the Chinese power sector, concluding that the current local air pollution control targets contributed slightly to the decrease of the carbon intensity in the power sector. Similarly, Kanada, Fujita et al. (2013) also empirically found that the air pollution control policy had a significant impact on the reduction of the industrial energy intensity in Kawasaki City, Japan. Hence, Fig. 2.7 implies that considering the health benefit of the tax will slightly increase the energy efficiency or the development of renewable energies to decrease the carbon intensity.

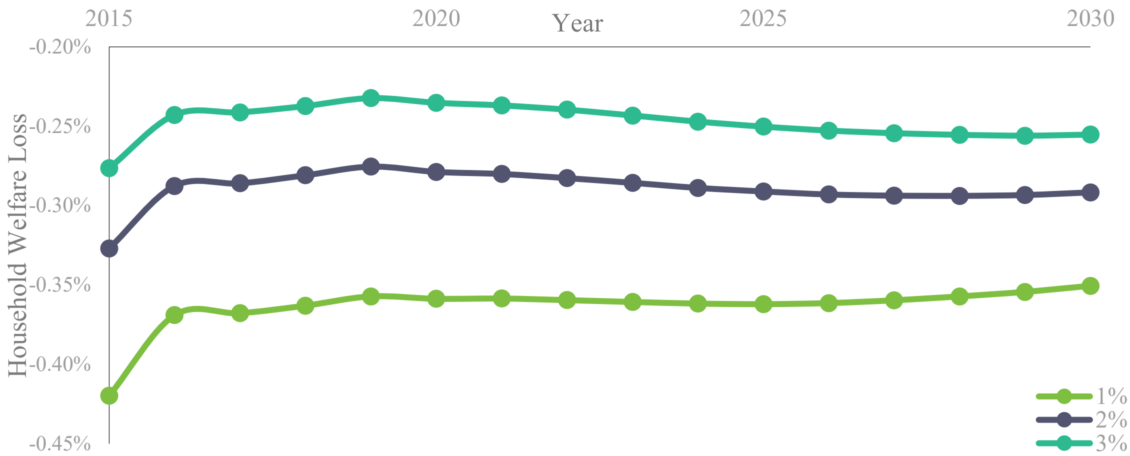


Fig. 2.8 The Health Benefit Impact on the Household Welfare Loss

Fig. 2.8 shows that the household welfare loss, induced by the carbon tax, will decline if the health benefit is considered. As the tax rate increases, this health benefit impact will decrease. Fig. 2.8 implies that ignoring the health benefit will overstate the true welfare effects of a climate policy. This is because the ill-health would pose a substantial threat to the household welfare (Quintussi, Van de Poel et al. 2015). This finding complies with Jensen, Keogh-Brown et al. (2013) who employed a single-country dynamic recursive CGE model and empirically found that the health co-benefits could improve the household welfare in UK. Similarly, Li (2006) also used a dynamic recursive CGE model and empirically found that including the health feedback would lead to better household welfare in Thailand. The economic intuition underlying Fig. 2.8 is that the health benefit will increase the labour productivity and thus labour income; finally, it will increase the household welfare.

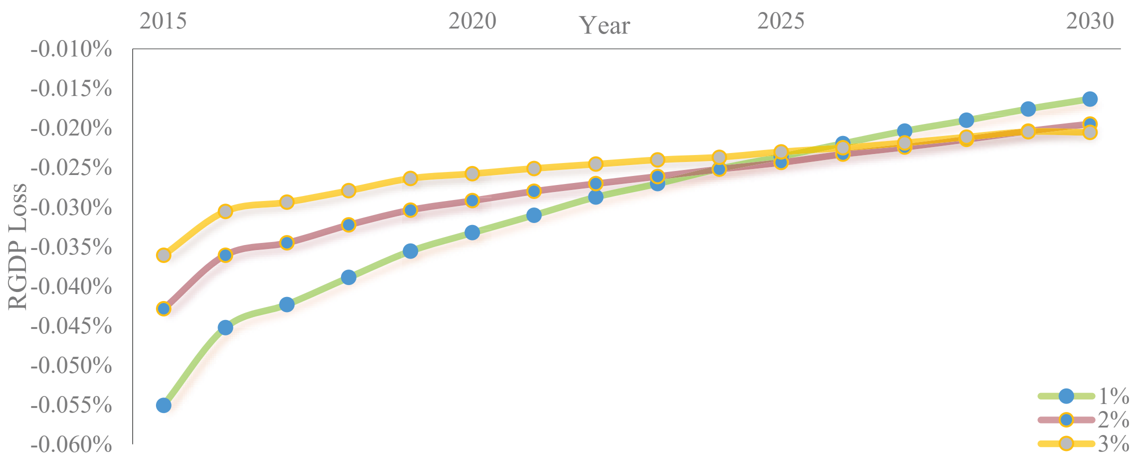


Fig. 2.9 The Health Benefit Impact on the Real GDP (RGDP) Loss

Compared to the household welfare, Fig. 2.9 shows that the health benefit will have a much smaller impact on the RGDP loss. In all the tax scenarios, the health benefit will reduce the RGDP loss and thus increase the RGDP, but this impact will decline over the studied period. Fig. 2.9 implies that this health benefit impact is minimal, and the health benefit is less attractive at the country level than the household level. This minimal health benefit impact could be explained by the mismatch between the sectors with the high potential for emission reductions and the sectors with the high health benefits per unit emission reduction (Liu, Huang et al. 2017). For example, the food, wood, and non-specified secondary industry had the highest health benefit per unit emission reduction but only contributed to less than 10% of the total emission reduction in the Chinese city of Suzhou (Liu, Huang et al. 2017). The magnitude of the health benefit impact in this chapter is much smaller than that in Balbus, Greenblatt et al. (2014). This is because Balbus, Greenblatt et al. (2014) estimated the population-level exposures based on the intake fractions, and the embedded assumptions and methodological choices explain why their empirical results were much more considerable than this chapter.

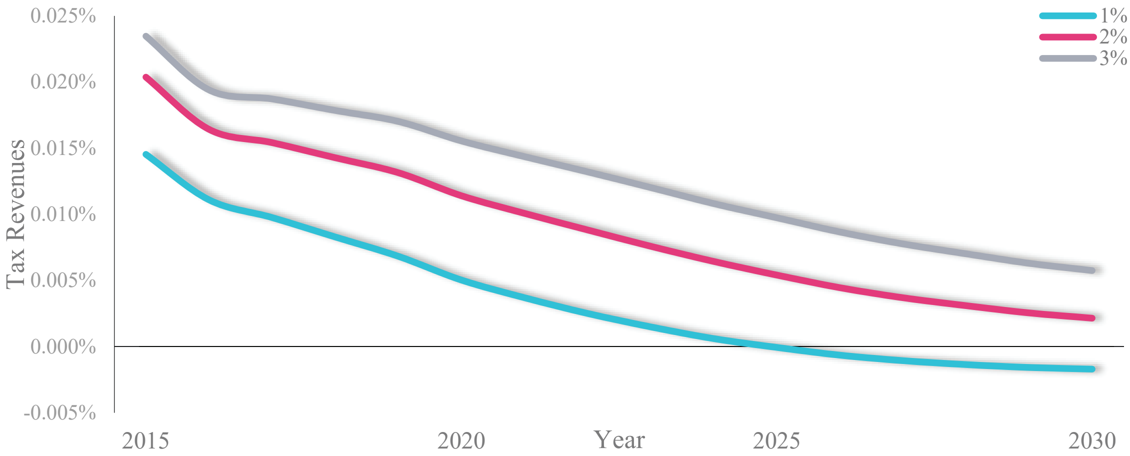


Fig. 2.10 The Health Benefit Impact on the Tax Revenues

Fig. 2.10 shows that the health benefit will induce more tax revenues in 2015–2024 and less tax revenues in 2025–2030 at the 1% tax. In contrast, the health benefit will increase the tax revenues over the studied period at the 2% and 3% tax. Fig. 2.10 implies that the health benefit will generally increase the tax revenues. This is because the health benefit will increase the labour productivity and thus promote the RGDP growth, which will finally increase the tax revenues. However, at the 1% tax, such economic boom will disappear in 2025–2030.

Fig. A2.1–A2.6 in Appendix A shows the health benefit impact on the recycling of the tax revenues where the tax rate is 1%. These graphs imply that the health benefit will have almost no impacts on the carbon emissions, carbon intensity, or social welfare when the tax revenues are recycled to the different economic entities. The small impacts of recycling the revenues, shown in the previous chapter, may explain these findings: because recycling the revenues has minimal impacts on the model equilibrium, the health benefit impact on the policy effects of recycling the revenues is also minimal.

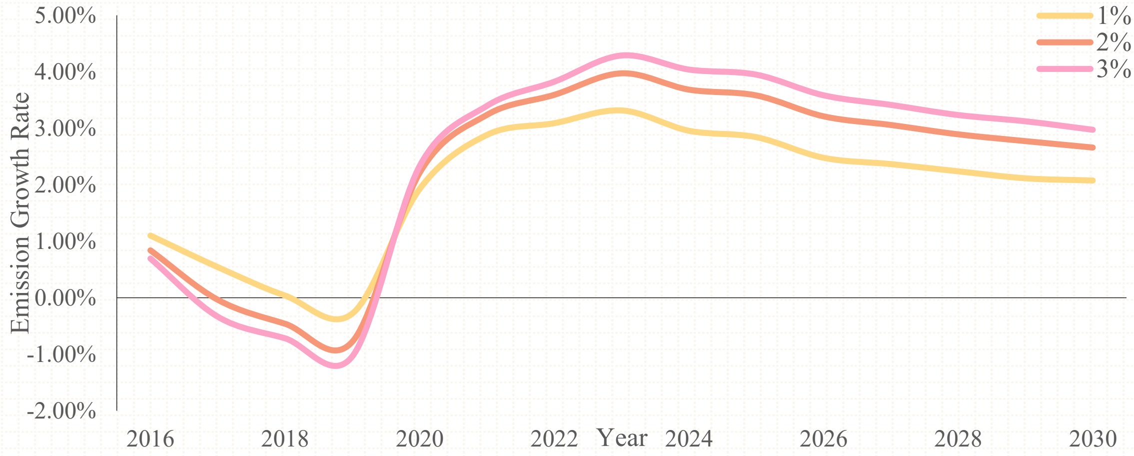


Fig. 2.11 The Total Emission Growth Rate in the Clean-air Model

Fig. 2.11 shows the total emission growth rate when the health benefit is considered. The emission growth rate will decline continuously since 2026. However, 2030 will not be the emission peaking point as the growth rate will not approach zero in that year. This trend is contrary to the INDC target of peaking the emissions in 2030. To achieve this target, China needs to take more steps to control its carbon emissions in addition to the carbon tax simulated in this chapter or I need to internalise other influential factors of the carbon tax in the policy evaluation framework. Nevertheless, Fig. 2.7 shows that the health benefit impact will decrease the carbon intensity, and the previous chapter shows China can meet the INDC target of the intensity reduction by 60–65% from the 2005 level in 2030. Hence, considering the health benefit impact, China can still meet this INDC target under the carbon tax.

The overall accomplishment of the INDC target of the carbon intensity reduction does not necessarily mean the accomplishment in all the sectors. A sectoral carbon intensity in 2030 is divided by its corresponding intensity in 2005, and the ratios are displayed in Table 2.2. As the sectoral energy consumption is assumed to be proportional to the corresponding sectoral output in this chapter, the carbon tax is assumed to have no effects on the sectoral carbon intensities. However, the carbon tax does affect the total carbon intensity. This is because the tax-induced rising energy price changes the household energy consumption, which varies the total energy consumption.

Table 2.2 The Sectoral Intensity Ratios in 2030 to 2005 (Unit: kg/CNY)

Sector	Ratio	Sector	Ratio	Sector	Ratio	Sector	Ratio
agric	35.65%	metal	40.35%	coking	36.87%	Supercrit	8.07%
othm	47.56%	machi	58.54%	petrm*	101.05%	USC	7.21%
food	21.93%	water*	752.18%	petrp	47.83%	Subc	5.81%
texti	45.30%	const	32.57%	gasn	44.49%	NG	22.36%
furni	26.19%	trans	45.22%	gasm	5.60%		
chemical	25.58%	service	36.03%	fipow*	87.26%		
mineral	38.62%	coalm*	95.19%	TD*	296.18%		

Note: * denotes the sectors that have a ratio larger than 65%.
Full sectoral names are shown in Table A1.1 in Appendix A.

Table 2.2 shows the sectoral intensity in 2030 relative to 2005 except that the electricity subsectors exploiting renewables are assumed to have zero carbon intensity. In most of the sectors, the 2030 intensity will be lower than 65% of the 2005 level except for the water production, coal mining, petrol extraction, heat production and distribution, and electricity transmission and distribution sector. Noticeably, the carbon intensity in the water production sector in 2030 will be approximately 7.5 times the 2005 level. As the energy consumption and sectoral output of the water production sector only take up a very small proportion to the national level, the influence of this sector on the overall intensity is quite small.

Results of the Sensitivity Analysis

Table 2.3 The Sensitivity Analysis of the Model Results in 2015

2015	-10%	-5%	-3%	-1%	1%	3%	5%	10%
HCE	0.096%	0.048%	0.029%	0.010%	-0.010%	-0.029%	-0.048%	-0.096%
TCE	0.005%	0.002%	0.001%	0.001%	0.000%	-0.001%	-0.002%	-0.005%
CI	-0.008%	-0.004%	-0.002%	-0.001%	0.001%	0.002%	0.004%	0.008%
HWL	-0.165%	-0.082%	-0.049%	-0.016%	0.016%	0.049%	0.082%	0.165%
TXR	0.006%	0.003%	0.002%	0.001%	-0.001%	-0.002%	-0.003%	-0.006%
RL	-0.021%	-0.011%	-0.006%	-0.002%	0.002%	0.006%	0.011%	0.021%

Table 2.4 The Sensitivity Analysis of the Model Results in 2030

2030	-10%	-5%	-3%	-1%	1%	3%	5%	10%
HCE	0.077%	0.039%	0.023%	0.008%	-0.008%	-0.023%	-0.039%	-0.078%
TCE	-0.002%	-0.001%	-0.001%	0.000%	0.000%	0.001%	0.001%	0.002%
CI	-0.005%	-0.003%	-0.002%	-0.001%	0.001%	0.002%	0.003%	0.005%
HWL	-0.199%	-0.100%	-0.060%	-0.020%	0.020%	0.060%	0.100%	0.200%
TXR	-0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%
RL	-0.009%	-0.005%	-0.003%	-0.001%	0.001%	0.003%	0.005%	0.009%

Note: HCE, TCE, CI, HWL, TXR, and RL denote the household emissions, total emissions, carbon intensity, household welfare loss, tax revenues, and RGDP Loss respectively.

Table 2.3 and 2.4 show the sensitivity analysis results in 2015 and 2030 respectively when the 1% carbon tax is imposed, and the tax revenues are kept in the governmental budget. According to these tables, the percentage changes of the model results are much lower than that of the parameter (the unit change of the labour productivity to the $PM_{2.5}$ pollution). The results of the sensitivity analysis imply that the model results in this chapter are quite robust to the parametric uncertainties.

Discussion

In this chapter, the health benefit is modelled as the increase of the labour productivity induced by the reduction of the $PM_{2.5}$ emissions. I have assumed that the labour productivity is linear to the $PM_{2.5}$ concentrations. However, this linear relationship may not exist in the reality. For example, Chang, Zivin et al. (2016) studied the impacts of outdoor air pollution on the productivity of the pear packers and empirically found that an increase in the $PM_{2.5}$ concentrations led to the significant decreases in the productivity with the impacts arising at the levels below the air quality standards. Similarly, Heyes and Zhu (2019) investigated a link from daily air pollution exposure to sleep loss in a panel of Chinese cities and empirically found that the daytime air pollution had a substantial impact on the sleep quality of the following night.

The labour productivity is also influenced by other air pollutants, such as SO_2, NO_x, and PM_{10}, in addition to $PM_{2.5}$. A climate policy that curbs the carbon emissions may also reduce the emissions of these air pollutants, and thus the health benefit in the reality can be much larger than the benefit this chapter has estimated. Therefore, a composite index, denoting the concentrations of all kinds of the air pollutants, may be conducive to revealing how the air pollutants will reduce the labour productivity more clearly.

The improved labour health is also beneficial to the human capital accumulation as the capital damages are assumed to be linear to the level of the air pollution (Bretschger and Karydas 2018). Future research may comprehensively explore how the air pollutant emissions will affect the human capital accumulation in the CGE policy evaluation framework. For example, the rise of the respiratory diseases, owing to the air pollution, will both increase the household and government medical expenditures, which will indirectly reduce the expenditures on the other items, given that the overall income is unchanged or even decreases.

As the health benefit is only part of the ancillary benefits, letting aside the primary benefits, an unbiased study needs to consider all the primary and ancillary benefits of climate policies. Even within the domain of the health benefits, the clean air can also improve the labour health by encouraging the active transportation choices, improving the ecosystems, and promoting the health equity in the society (Ambasta and Buonocore 2018). If all the benefits had been considered, many climate policies would have been deemed to increase the social welfare. In this case, the carbon tax rate can be defined as an endogenous variable to find out the optimum policy which will maximise the social welfare.

The carbon tax is assumed to be technical neutral in this chapter, which implies that the tax has no effects on the sectoral carbon intensities. However, in the reality, the carbon tax is likely to promote the technical progress and thus increase the efficiency of the energy use or enhance the development of the renewable energies. Hence, the carbon tax might decrease the sectoral carbon intensities.

Policy Implications

The ancillary (health) benefit will slightly weaken the policy effects of the carbon tax; in other words, the ancillary benefit will increase the carbon emissions but decrease the household welfare and real GDP loss, induced by the carbon tax. The ancillary benefit has almost no impacts on the policy effects of recycling the tax revenues or the marginal effects of the carbon tax. The ancillary benefit does not affect how China will accomplish the INDC targets.

Conclusion

In this chapter, the quantified ancillary benefit of the carbon tax is the health benefit from the reduction of the $PM_{2.5}$ pollution. The health benefit will increase the household carbon emissions by 0.15%–0.4% depending on the tax rate and time. The health benefit will decrease the household welfare and real GDP loss, induced by the carbon tax, by 0.2%–0.45% and 0.015%–0.055% respectively. Nevertheless, the health benefit has almost no impacts on the policy effects of recycling the tax revenues. The minimal impacts of the health benefit on the policy effects of the carbon tax imply that the inclusion of the other types of ancillary benefits could significantly affect the model equilibrium. With the health benefit, the carbon tax alone cannot help China meet the INDC target of peaking the emissions before 2030 but can meet the target of the intensity reduction. Most sectoral carbon intensities in 2030 will be lower than 65% of the 2005 level, and thus the intensity reduction target can be met in most sectors. The sensitivity analysis implies that the model results are quite insensitive to the given value of the parameter (unit change of the labour productivity to $PM_{2.5}$ pollution).

Chapter 3: The Primary Benefit of the Carbon Tax

Introduction

As the climate change has strong roots in the natural sciences and requires social sciences to solve in an effective manner, the primary aim of climate policies is climate protection in order to prevent climate-change-induced damages (Rubbelke 2006). Hence, primary benefits, also known as climate benefits or direct benefits, of climate policies refer to the avoided damages from the accelerating climate change (Lomborg 2020). Primary benefits include the reduction of the extreme weather and short-lived climate pollutants (SLCP), contributing significantly to the radiative forcing that drives climate change (Pierrehumbert 2014). Climate policies are also beneficial to reducing the negative impacts of the rising sea-level induced by the climate change (Farquharson, Jaramillo et al. 2017).

Previously, a great deal of research has empirically documented the primary benefits of climate policies, and the evidence could be found worldwide. For example, Melvin, Sarofim et al. (2016) used the Environmental Protection Agency (EPA) data to show that the US climate policy generated climate benefits; Trotta (2020) assessed the climate benefits induced from energy efficiency improvements in Finland by performing the multi-sectoral decomposition analysis. These two studies only analysed the climate benefits in a partial equilibrium setting and thus may not comprehensively answer to what extent the primary benefits affect the socioeconomic and emission effects of climate policies.

Some studies mixed the primary benefits with the ancillary benefits when analysing the effects of climate policies. For example, Siler-Evans, Azevedo et al. (2013) gathered the emission data of fossil-fueled power plants but only quantified the combined health, environmental, and climate benefits of wind and solar generation. Similarly, Buonocore, Luckow et al. (2016) utilised a high-resolution model but only analysed the total health and climate benefits of different energy-efficiency and renewable energy choices but did not indicate the specific value of climate benefits. The mixture of the benefits in the literature corresponds to the fact that the primary benefits of climate policies are even harder to model, compared to the ancillary benefits (Baker, Collins et al. 2015).

Previous studies that only measured the mixed benefits are likely to underestimate the primary benefits of climate policies. For example, Wang, Huang et al. (2020) assessed the synergy between climate policies and air pollution, focusing on the economic and household income impact from the health and labour market perspective (Wang, Huang et al. 2020). As labour health and supply are directly linked to air pollution but indirectly affected by the climate change (Robinson 2014), Wang, Huang et al. (2020) is likely to overestimate the impacts of the ancillary benefits and underestimate the impacts of the primary benefits. Because of the difficulties in the quantification, the primary benefits of climate policies only play a minor role in the political agenda of the developing countries including

China, even though the industrialised countries have a strong interest in combating the climate change (Rubbelke 2006).

The underestimation of the primary benefits is likely to result in the reluctance of governmental policy implementation (Baker, Collins et al. 2015). The unpopularity of climate policies justifies the increasing necessities to quantify primary benefits separately from ancillary benefits (Nordhaus 2018). The primary benefits of climate policies can be modelled by integrated assessment models (IAMs), which are used to study earth systemwide climate changes and the effects of public policies on the projected future climate change (Weyant 2017). The Dismal Theorem implies that IAMs cannot be used to determine an optimal climate policy because prior knowledge cannot place sufficiently narrow bounds on the overall damages of a climate catastrophe (Weitzman 2009). However, the conditions necessary for the Dismal Theorem to hold are limited and inapplicable to many potential uncertain scenarios (Nordhaus 2011). Hence, IAMs are widely applied in the literature to study the effects of climate policies on the climate change (Weyant 2017), because they can "provide conceptual frameworks for developing insights about highly complex, nonlinear, dynamic, and uncertain systems" (Weyant 2017).

Previously, the three most widely used IAMs are: Dynamic Integrated model of Climate and the Economy (DICE) or Regional Integrated model of Climate and the Economy (RICE) model, deriving from Nordhaus (1992); Policy Analysis of the Greenhouse Effect (PAGE) model, shown in (Hope 2013); Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) model, co-developed by Anthoff and Tol (2013). These IAMs have been used to find out the optimal climate policy considering the socioeconomic impacts of the climate change in the literature (Weyant 2017). The PAGE model has a relatively simple economic structure but detailed inventories of greenhouse gases (Hope 2013). As the CGE model is used to analyse the economic structure of China in the previous chapters and the targeted greenhouse gas is carbon dioxide only, therefore, the DICE model is preferable in this chapter. The FUND model gives more detailed impacts of the climate change, including the impacts on the agriculture, forestry, sea level rise, dengue fever, and schistosomiasis (Waldhoff, Anthoff et al. 2014), but it is considerably more complex than the other two IAMs (Anthoff and Tol 2013). In contrast, the DICE model captures the earth geophysical system using only a few simple equations, but the model has no distinct differences in the major environmental variables compared to the other IAMs (Nordhaus 2018). In addition, the FUND model and PAGE model are run in the Julia software, whilst the DICE/RICE model is run in the GAMS software. Therefore, the DICE model is technically compatible with the CGE model presented in the earlier chapters. Hence, in this chapter, a DICE/RICE model is used to quantify the primary benefits of the carbon tax. The latest published DICE model is the DICE-2016R2 (Nordhaus 2018), and the GAMS code of the model is available on the homepage of Nordhaus's personal website.

As the main research framework of this paper is the CGE model, this chapter will not make direct contributions to the development of the Chinese IAMs in the literature. Nevertheless, this chapter contributes to the literature by innovatively modelling the primary benefits of the Chinese carbon tax, using the DICE/RICE model, within the CGE framework of the policy evaluations. Very little previous research has unbiasedly modelled the primary benefits of climate policies in the policy evaluations, because the climate benefits from a local carbon emission reduction are usually distributed spatially beyond the local region (Lee, Shindell et al. 2016). To my best knowledge, this chapter is the first attempt to model the climate benefits of the Chinese carbon tax as a part of the potential policy benefits in addition to the ancillary benefit defined in the previous chapter.

In this chapter, how the primary benefits influence the policy effects of the carbon tax is analysed via the result comparison of the CGE-DICE model, defined in this chapter, and the clean-air model, defined in the previous chapter. As modelling the primary benefits is susceptible to the exogenous values of the geophysical parameters, a sensitivity analysis has been conducted to show to what extent the model results are robust to the parameters given by the DICE/RICE model. If the results are not subject to the changes of the parametric values, the geophysical equations explain the authentic impacts of the primary benefits on the model equilibrium. On the contrary, those parameters that lay undue influences on the results need to be identified.

Method

If analysed alone, the socioeconomic impacts of the climate change could be very small; indeed, the impact of the climate change in a century is roughly equivalent to a year's growth in the global economy (Tol 2013). Hence, in this chapter, the aforementioned CGE model is used to analyse the ancillary benefits of the carbon tax in combination with the DICE/RICE model to quantify the primary benefit of the carbon tax simulated in this chapter.

According to Nordhaus (2018), the geophysical variables are quite stable in the development of the DICE/RICE models because modelling environmental components was based on a solid scientific foundation as the environmental issues were relatively well-understood by the early 1990s. In contrast, the dominant underlying changes in the DICE/RICE model results lie in the economic variables (Nordhaus 2018) because of a major change in the projected global productivity growth (Nordhaus 2018). Therefore, it is preferable to model regional economy separately. Even though the economic equations in the CGE model of this chapter is targeted at China only, the anthropogenic emissions in China has a global effect on the climate and thus the geophysical equations targeted globally in Nordhaus (2018) are kept in this chapter. These geophysical equations are used to analyse how the primary benefits of the carbon tax affect the CGE model equilibrium where the household welfare is introduced as the optimised target.

According to Nordhaus (2018), the net consumption goods are defined as the aggregation of the monetary values of the consumption goods minus the abatement costs and damages from the climate change over the research period. In Eq. (3.1), Q_t is the net consumption goods in Year t; $damfrac_t$ is the damage function shown in Eq. (3.2); Λ_t is the abatement cost ratio shown in Eq. (3.3); THD_t refers to the monetary value of the consumption goods in Year t calculated in the CGE model.

$$Q_t = THD_t \times (1 - damfrac_t) \times (1 - \Lambda_t) \tag{3.1}$$

$$damfrac_t = \psi_1 T_t^{AT} + \psi_2 (T_t^{AT})^2 \tag{3.2}$$

$$\Lambda_t = \theta_{1t} \times {\mu_t}^{\theta_2} \tag{3.3}$$

In Eq. (3.2), T_t^{AT} refers to the global mean surface temperature in Year t; ψ_1 and ψ_2 are the parameters measuring how the global temperature rise induces welfare loss. In Eq. (3.3), $\theta_{1t} = 0.0741 \times 0.0904^{t-1}$ and $\theta_2 = 2.6$. μ_t describes the proportion of the reduced emissions to the total industrial emissions in China resulting from the carbon tax.

$$HW = \sum_{2015}^{2030} {c_t}^{1-\eta}/(1-\eta) \times Pop_t \times (1+\delta)^{-t} \tag{3.4}$$

Eq. (3.4) shows the definition of the household welfare (HW) in China. c_t is the per capita consumption in Year t. The parameter η measures the elasticity of the marginal utility of consumption, and it is interpreted as the generational inequality aversion with its value 1.45 according to Nordhaus (2018). Pop_t is the Chinese population in Year t, and the predicted data are from 2017 World Population Prospects (WPP) by UN (2017). The parameter δ refers to the social time preference on the welfare, and its value is 1.5% given by the DICE-2016R2 model. In this chapter, the change of the household welfare is used to denote the policy effects of the carbon tax. From the household perspective, an optimum policy induces the largest increase of the welfare. Hence, the carbon tax rate is endogenously determined in the DICE model, whilst the tax rate is an exogenous variable in the CGE model.

In this chapter, I have used the geophysical equations in the DICE/RICE models with some modifications. As the DICE or RICE models have almost the same geophysical equations, I make citations from the DICE models in the context below. The world carbon emissions (WE_t) is defined as the summation of industrial emissions in China (CE_t), industrial emissions in the rest of the world (RWE_t) and the global exogenous land-use emissions (E_t^{Land}). By comparison, in the DICE-2016R2 model, the world carbon emissions are defined as the summation of global industrial emission and land-use emissions. In this chapter, the CE_t projection is specified by the CGE model, whilst RWE_t and E_t^{Land} are assumed to follow the projection route of WE_t and E_t^{Land} respectively specified in the DICE-2016R2 model. This assumption implies that RWE_t and $E_t^{Land}$are exogenously determined, and their values will not change irrespective of the carbon tax simulated in this chapter.

In the DICE model, the global industrial and land-use emission data are based on the Nordhaus (2018), whose data were mainly from the Carbon Dioxide Information Analysis Centre (CDIAC) but updated using various sources. According to the CDIAC (2016) data, China and the RW emitted 10.37 Gt CO_2 and 25.93 Gt CO_2 respectively in 2015. The CDIAC (2016) data provide the proportion of the Chinese emissions to the RW emissions in the base year (2015). Because the calculated Chinse emission data from the CGE model are different from the CDIAC data, I have adjusted the RW emission data in CDIAC (2016) by the aforementioned proportion.

The carbon tax is assumed to affect the Chinese industrial emissions only, and it does not affect the industrial emissions in the rest of the world. Although researchers empirically confirmed the existence of carbon leakage between an Emission Trading Scheme (ETS) pilot site and the rest of China (Tan, Liu et al. 2018, Wang, Teng et al. 2018), no carbon leakage exists for all the Chinese sectors on the whole (Fan, Zhang et al. 2019). Similarly, Fu and Zhang (2015) used the industry panel data in 1996–2010 and concluded that no carbon leakage existed for the whole manufacturing industry, whilst Zhao (2014) used the import and export data and empirically found that there was no clear evidence of carbon leakage from America to China. Hence, in this chapter, the carbon leakage is assumed to have no impacts on the emissions in China or rest of the world (RW).

$$M_{jt} = \phi_0 WE_t + \sum_{k=1}^{3} \phi_{kj} M_{k(t-1)} \tag{3.5}$$

Eq. (3.5) shows the carbon cycle of the three defined reservoirs, where the subscript j equals AT, UP, and LO, referring to the three reservoirs: the atmosphere, the upper oceans and biosphere, and the lower oceans respectively. ϕ_{kj} is the flow parameter from Reservoir k to j; ϕ_0 is the flow parameter denoting how the global emissions are deposited; M_{jt} is the accumulated carbon dioxide of Reservoir j in Year t.

$$F_t = \eta\{\log_2[M_t^{AT}/M_{1750}^{AT}]\} + F_t^{EX} \tag{3.6}$$

Eq. (3.6) quantifies the increase of the radiative forcing caused by the accumulation of the carbon dioxide, where F_t denotes the change of the radiative forcing from the anthropogenic emissions; F_t^{EX} is the exogenous forcing; η is the parameter measuring how the atmospheric carbon dioxide concentrations affect the radiative forcing; M_t^{AT} is the accumulated carbon dioxide in the AT reservoir; M_{1750}^{AT} is the value of M_t^{AT} in 1750.

$$T_t^{AT} = T_{t-1}^{AT} + \xi_1\{F_t - \xi_2 T_{t-1}^{AT} - \xi_3[T_{t-1}^{AT} - T_{t-1}^{LO}]\} \tag{3.7}$$

$$T_t^{LO} = T_{t-1}^{LO} + \xi_4[T_{t-1}^{AT} - T_{t-1}^{LO}] \tag{3.8}$$

Eq. (3.7) and (3.8) show how the radiative forcing leads to the global warming, where T_t^{AT} is the global mean surface temperature in Year t; T_t^{LO} is the global mean temperature of the lower oceans in Year t; ξ_1, ξ_2, ξ_3, and ξ_4 are all exogenous parameters, and their values are given by the DICE model.

The time interval in this chapter is one year, whereas the time interval in the DICE-2016R2 model is five years. The GAMS code for the DICE model needs to be revised to accommodate the change of the time interval in this chapter. The RW emissions in a five-year period are assumed to change linearly according to the baseline scenario of the global industrial emissions in the DICE-2016R2 model.

The global output data in the DICE-2016R2 model is 2005 USD, while the real GDP (RGDP) data in the CGE model is 2015 CNY. To accommodate the unit difference, the abatement cost data calculated by the DICE model is multiplied by the exchange rate of USD to CNY in 2005 and the relative price of 2015 to 2005 in China according to the NBS (2017) data.

To analyse the primary-benefit impacts of climate policies, in this chapter, I compare the results of the two models: the clean-air model, defined in the previous chapter excluding the primary benefits, and the CGE-DICE model, defined in this chapter including the primary benefits. In the CGE-DICE model, $PM_{2.5}$ pollution deducted labour productivity rate (PML_t) was redefined as the effective labour productivity rate (ELP_t). ELP_t considers not only the reduction of the air pollution but also the reduction of the climate damages induced by a climate policy. In Eq. (3.9), Dam_t refers to the climate damages in Year t; $Dam0_t$ refers to the baseline climate damages in Year t, and its value was obtained by running the GAMS code of the baseline scenario of the control model.

$$ELP_t = \begin{cases} 1 - \left(26.91 + 32.16 \times \frac{TCE_t}{TCE0_t} \times \frac{Dam_t}{Dam0_t}\right) \times 0.14\% & \mathrm{t} = 2015 \\ 1 - \left(23.79 + 28.43 \times \frac{TCE_t}{TCE0_t} \times \frac{Dam_t}{Dam0_t}\right) \times 0.14\% & \mathrm{t} = 2016 \\ 1 - \left(23.99 + 28.67 \times \frac{PME_t}{PME_{2017}} \times \frac{TCE_t}{TCE0_t} \times \frac{Dam_t}{Dam0_t}\right) \times 0.14\% & \mathrm{t} \geq 2017 \end{cases} \quad (3.9)$$

The comparison between the two models will reveal how the primary benefit affects the policy effects of the carbon tax. In the baseline scenario, the household emissions, total emissions, carbon intensity and real GDP (RGDP) are all the same in the two models. However, when the carbon tax is imposed, the results in the two models may become different.

The embedded assumption of the above analysis is that all the sectors exploiting nonrenewable energies are faced with the same given exogenous tax rates. To relax this assumption, the tax rate is endogenized to find out the optimum tax rate that maximises the household welfare. In the endogenization, the tax rate can change freely from 0 to 5%. The upper bounds of the labour, capital and energy inputs are equal to the corresponding baseline inputs. The lower bounds of the inputs are set to 1% of the baseline inputs, which are less than the inputs if a 5% tax is imposed.

The social cost of carbon (SCC) refers to the present value of the costs paid by the present and future generations due to the emissions of an additional tonne of carbon dioxide today (Fleurbaey, Ferranna et al. 2019). The socially optimal carbon price is the smallest SCC that can achieve the abatement target (Tang, Ji et al. 2020). In the literature, many researchers designed socially optimal carbon taxes basing on the SCC (Belfiori 2017, Belfiori 2018, Linnenluecke, Smith et al. 2018). However, the estimated SCC ranged from approximately \$10 to well over \$200 per metric ton, but hardly a consensus number has been reached (Pindyck 2019). The inability to reach the consensus partially explains why international climate negotiations have focused on intermediate targets (Pindyck 2017). Binding the carbon price to quantitative targets by climate policies is the only way to ensure the effectiveness of carbon pricing (Boyce 2018). Hence, in this chapter, the SCC is analysed under China's INDC target.

Nordhaus (2017) defined the SCC as the marginal welfare impact of the emissions divided by the marginal welfare impact of the total consumption, which is a way to denote the economic impacts of the emissions. However, the definition of Nordhaus (2017) lacks the analysis of the uncertainty of the discount rate, the choice of which has a significant influence on the final estimate of the SCC (Guo, Cameron et al. 2006). According to Pindyck (2017), the marginal SCC has three main drawbacks: it is time-variant, and thus the optimal policy will change over time; it has a very limited guidance for the current policy; it has an extreme sensitivity to the discount rate. By comparison, the average SCC is less sensitive to the baseline time path for the carbon emissions, provides a guideline over an extended time period, and is much less sensitive to the choice of the discount rate (Pindyck 2019). In this chapter, the polynomial expression of the average SCC is from Tian, Ye et al. (2019) who analysed the uncertainties of the model related to the discount rate, carbon cycle, climate sensitivity, and damage parameters. Tol (2013) believed that the SCC is also affected by the aforementioned four parameters.

$$SCCtotal_t = \chi R\dot{GDP}_t \sum_{k \in K} \frac{a_k \epsilon}{(\eta_k + r)(\epsilon + r)} \left(1 - \frac{2E_t}{n \times E^{sum}}\right) \tag{3.10}$$

$$ASCC_t = SCCtotal_t / E_t \tag{3.11}$$

$$R\dot{GDP}_t = RGDP_t \times (1 - damfrac_t) \times (1 - \Lambda_t) \tag{3.12}$$

In Eq. (3.10) to (3.12), $SCCtotal_t$ and $ASCC_t$ stand for the total and average social cost of carbon respectively. $R\dot{GDP}_t$ is the net RGDP in Year t, defined as the RGDP minus the climate damages and abatement costs. χ is the damage sensitivity coefficient to the increase of the carbon dioxide in the atmosphere, and its value is 0.00236 (Nordhaus 2017). ϵ is the equilibrium temperature sensitivity, and its value is 3.1 (Nordhaus 2017). n is the evolutionary coefficient of the carbon emissions, and its value is set to one (Tian, Ye et al. 2019). E^{sum} denotes the maximum carbon emissions, and it is equal to the summation of the annual carbon emissions over the research period. Following Tian, Ye et al. (2019), a_k and η_k refer to the vector shares of the carbon emissions entering the climate box and the attenuation rate of the climate box respectively. The values of a_k and η_k are from the DICE model, shown in Table 3.1.

Table 3.1 The Parametric Values of a_k and η_k

	1st Value	2nd Value	3rd Value
a_k	0.029	0.356	0.615
η_k	0	0.0035	0.0364

In Eq. (3.10), r refers to the social discount rate, which shows how the values of future goods and services are discounted relative to their present values (Snyder 2020). Debates about the discount rate have a long history in economics and social policies (Nordhaus 2007). Researchers still remain sceptical about what rate should be used for discounting the climate change (Weitzman 2007). Hence, the choice of the discount rate has significant impacts on the SCC estimates (Snyder 2020). In this chapter, the relation of the SCC and discount rate is compared between China and the US. The United States Environmental Protection Agency (EPA) published the US average social cost of carbon (ASCC), but the unit of the data is 2007 dollars per metric ton CO_2. In this chapter, the US data are adjusted with the relative price of 2007 to 2015, using the consumer price index in the World Development Indictors according to World Bank (WB).

According to Tian, Ye et al. (2019), the social discount rate r is defined in Eq. (3.13). δ denotes the pure time preference rate, and its value is 0.015 (Nordhaus 2017). ξ_{co} is the elasticity of marginal utility of consumption, and its value is 1.45 (Nordhaus 2017). ξ_{in} is the damage income elasticity, and its value is 1.15 (van den Bijgaart, Gerlagh et al. 2016). g represents the average growth rate of consumption, and its value is 5.5% (Tian, Ye et al. 2019). l is the average population growth rate, and its value is 0.6% given by Tian, Ye et al. (2019).

$$r = \delta + (\xi_{co} - \xi_{in}) \times g - l \tag{3.13}$$

The definition of the social discount rate in Tian, Ye et al. (2019) is time-invariant. However, the discount rate could vary with the time according to the classical Ramsey (1928) formula, show in Eq. (3.14). This is because the consumption changes as the time goes by.

$$r_t = \delta + \eta \times g_t \tag{3.14}$$

In Eq. (3.14), δ refers to the pure time preference rate; g_t refers to the consumption growth rate in Year t; r_t refers to social discount rate in Year t. η measures the elasticity of the marginal utility of consumption, but it is interpreted as the inequality parameter in the welfare function of the DICE model (Nordhaus 2018). The inequality parameter denotes an aversion to inequality in consumption that is independent of whether the inequality is across contemporaries or across time, according to Dennig, Budolfson et al. (2015) who introduced a fine-grained representation of economic inequalities in the RICE model. A low value of the inequality parameter means that the consumptions of different generations are close substitutes, with low aversion to inequality, whilst a high value of the inequality parameter denotes the highly differentiated consumptions and thus high generational inequality aversion (Nordhaus and Sztorc 2013).

In the literature, standard models in the welfare economics regard the parameter η as the simultaneous representation of risk, time and space (Atkinson, Dietz et al. 2009): “risk” measures the uncertainties about the impacts of climate change which may be large and irresolvable (Stern 2007). “Time” means the intergenerational inequality. “Space” measures the spatial disparities in the relative impacts of climate change (IPCC 2007), and thus it is also called the intragenerational inequality. However, in the context of the climate change, the correlations between preferences over these three dimensions are weak, according to Atkinson, Dietz et al. (2009) who surveyed the attitudes of over 3000 people. Hence, the dimensional correlations need to be explored further in the analysis of climate policies. More recently, Emmerling (2018) explored the inequality dimensions within an emphasis on the intragenerational inequality across countries. As only the impacts of climate change in China are analysed in this chapter, the intragenerational inequality worldwide is omitted. However, intrageneration inequality exists within China, but it coincides with the income inequality analysed in the context above. To separate the risk from the time denoted by η in Eq. (3.14), Eq. (3.15) is employed according to Traeger (2009). In Eq. (3.15), η denotes the aversion to intertemporal fluctuations only.

$$r_t = \delta + \eta \times g_t - \eta^2 \times \frac{{\sigma_1}^2}{2} - RIRA_t \times |1-\eta^2| \times \frac{{\sigma_1}^2}{2} \tag{3.15}$$

$$RIRA_t = \begin{cases} 1 - \frac{1-RRA}{1-\eta}, 1-\eta > 0 \\ \infty, \qquad\qquad 1-\eta = 0 \\ \frac{1-RRA}{1-\eta} - 1, 1-\eta < 0 \end{cases} \tag{3.16}$$

In Eq. (3.15), the parameter $RIRA_t$ characterises intertemporal risk aversion in Year t; the parameter σ_1 refers to the standard deviation of the growth rate, assuming that the growth rate is normally distributed. In the context of isoelastic welfare function defined in this chapter, the value of $RIRA$ is given by Eq. (3.16). In Eq. (3.16), RRA refers to the Arrow-Pratt relative risk aversion, and its best-guess value is 9.5 given by Vissing-Jorgensen and Attanasio (2003). By employing a stochastic version of the DICE model, Crost and Traeger (2014) also used RRA to compute the optimal carbon tax and abatement levels that maximise social welfare in the US. Because the absolute value in Eq. (3.15) is uneasy for calculation, Eq. (3.17) is introduced via combining Eq. (3.15) and (3.16).

$$r_t = \delta + \eta \times g_t - {\eta_t}^2 \times \frac{\sigma^2}{2} - (1 - \frac{1-RRA}{1-\eta}) \times (1-\eta^2) \times \frac{\sigma^2}{2} \tag{3.17}$$

$$g_t = THD_t/THD_{t-1} - 1 \tag{3.18}$$

$$\sigma = \sqrt{\frac{1}{16-1} \times \sum_{t=2015}^{2030} (g_t - \frac{1}{16} \times \sum_{t=2015}^{2030} g_t)^2} \tag{3.19}$$

In Eq. (3.17), according to Nordhaus (2017), the pure time preference rate (δ) equals 0.015. The generational inequality parameter η is time-invariant and equals 1.45. The consumption growth rate g_t is defined in Eq. (3.18) where THD_t refers to the total household consumption in Year t. The growth rate in the base year 2015 is calculated as the base year household consumption divided by the consumption in 2014. The 2014 consumption data is calculated using the 2012 and 2015 China Input-Output Table on the assumption that the household consumption changed linearly from 2012 to 2015. After the growth rate is calculated, its standard deviation σ is calculated using Eq. (3.19).

Nordhaus (2018) defined the social discount rate in the DICE model only using the parameter of the pure time preference rate δ show in Eq. (3.20). Because r_t in Eq. (3.20) is only related to δ, its value remains unchanged irrespective of the imposition of the carbon tax. Eq. (3.20) also implies that the future generation will have a larger value of r_t, which means the welfare of the future generation is less important than that of the current generation. Hence, the definition of r_t in the DICE model is likely to induce intergenerational inequality. In contrast, r_t defined in Eq. (3.15) of this chapter is influenced by a climate policy. This is because a climate policy may change the growth and standard deviation of the total consumption. Also, the definition of r_t in Eq. (3.15) shows no obvious discrimination on the welfare of the future generation regarding the total welfare.

$$r_t = 1 - \frac{1}{(1+\delta)^{t-2015}} \tag{3.20}$$

According to Price (2000), the social discount rate can be positive, zero, or negative, depending on the income growth rate, the investment return rate and so on. In this chapter, the social discount rate mainly depends on the consumption growth rate as the values of δ and η are fixed. A positive discount rate denotes the case of economic growth, while a negative rate is the case of a recession (Hellweg, Hofstetter et al. 2003).

$$HW = \begin{cases} \sum_{t=2015}^{2030} \left[POP_t \times (1 - r_t) \times \frac{(THD_t/POP_t)^{1-\eta} - 1}{1-\eta}\right], \eta \neq 1 \\ \sum_{t=2015}^{2030} [POP_t \times (1 - r_t) \times \ln (THD_t/POP_t)], \eta = 1 \end{cases} \tag{3.21}$$

The isoelastic welfare function defined in the DICE model includes the social discount rate r_t, shown in Eq. (3.21). HW is the household welfare; POP_t refers to the population in Year t. If the definition of r_t changes, its value will change, and thus the household welfare will also change.

Sensitivity Analysis

I have analysed how the major exogenously determined parameters will affect the model results based on Nordhaus (2018) who investigated the uncertainties of the DICE model. The uncertainty analysis in Nordhaus (2018) is quite similar to the sensitivity test of the CGE model. As the relative uncertainty is much higher for the economic variables than for the geophysical variables (Nordhaus 2018), only the geophysical equations of the DICE model are used in this chapter. Therefore, a sensitivity test has been conducted to analyse the impacts of the uncertainties existing in the geophysical parameters on the model equilibrium. Noticeably, the cumulative industrial emissions in this chapter are defined as the summation of the Chinese emissions plus the exogenous RW emissions over the research period. As the definition of the cumulative industrial emissions is irrelevant to the geophysical parameters, the sensitivity analysis on this variable is not performed in this chapter.

Nordhaus (2018) used a Monte Carlo simulation to estimate the distribution of the five parameters: the equilibrium temperature sensitivity, productivity growth, damage function, carbon cycle, and decarbonisation rate. In this chapter, the productivity growth and decarbonisation rate, namely the reduction of the carbon intensity, are endogenously determined by the CGE model. Hence, these two parameters are excluded in the sensitivity test. According to Nordhaus (2018), the probability density function (PDF) for each uncertain variable is divided into quintiles, and the expected values of the parameters in each quintile are shown in Table 3.2.

Table 3.2 The Quintiles of the Parameters

	Q1	Q2	Q3	Q4	Q5
KKdam	0.00061	0.00141	0.00236	0.00242	0.00464
KKets	2.00767	2.51586	3.1	3.38802	4.49126
KKcarb	233.59	292.95	360	394.35	519.33

Table 3.2 shows the quintiles of the parametric values defined in Nordhaus (2018). In Table 3.2, Q1–Q5 are the quantile points of the PDFs. KKdam is the coefficient for the damage equation, and an increase in KKdam means that the rising global temperature will give rise to more climate damages. KKets denotes the equilibrium temperature sensitivity or climate sensitivity, and it is defined as the equilibrium near-surface temperature response to a doubling of atmospheric CO_2 (Olson, Sriver et al. 2012). KKcarb measures the size of the intermediate reservoir (biosphere and upper level of the oceans) in the carbon cycle, which affects the atmospheric retention of the greenhouse gases over the medium term (Nordhaus 2018). The parametric values of Q3 are equivalent to the values of the best-guess case in the DICE model.

Nordhaus used the parameter η to denote the elasticity of marginal utility of consumption (Nordhaus 2017) and generational inequality aversion (Nordhaus 2018) interchangeably. This interchangeable use implies that the parameter η in the DICE/RICE model measures a combined effect of the intragenerational and intergenerational inequality as well as the marginal utility of consumption, which is unclear and confusing. In Eq. (3.21), the parameter η is supposed to measure the intertemporal aversion only. Hence, using the value of 1.45 given by Nordhaus (2018) may generate a biased estimation of the welfare.

In the literature, other researchers have argued for different values of η. For example, Stern (2007) argued for the immediate action to mitigate the climate change and suggested the value of η should be one. Weitzman (2007) showed $\eta = 2$ using the geometric-average point estimate. Similarly, Nordhaus (2007) argued that the value of η should be 2 in the early version of the DICE model. Dasgupta (2008) mentioned that the value of η could vary 1.5 to 3 worldwide. Cline (2010) argued that the value of η consistent with observed progressive tax systems was 1.5: a higher value would lead to the prohibitive taxes on the rich and a lower value would induce the non-progressive proportional taxation. Vissing-Jorgensen and Attanasio (2003) gave the best guess of η equal to $\frac{2}{3}$. In this chapter, the listed η values mentioned above will be included to analyse the impacts on the model results.

In this chapter, the default value of the pure time preference rate (δ) is 0.015 according to Nordhaus (2007) who argued for a low and positive discount rate to calibrate the utility function in the DICE model. In contrast, Weitzman (2007) thought that the decent parametric values would be a "trio of twos", arguing that δ should be 0.02. However, δ can be also 0.001, according to Stern (2007) who believed that the lowest conceivable value of δ should be used to denote social discounting. Similarly, Emmerling (2018) also used 0.001 as the value of δ to study the social discount rate considering intragenerational inequality. Nevertheless, δ was assumed to be 0 in Yamaguchi (2019) who decomposed the consumption discount rate. Hence, there are uncertainties in the parametric value of δ, and I will perform the sensitivity analysis to study how the uncertainties of δ will affect the utility (household welfare).

Model Results

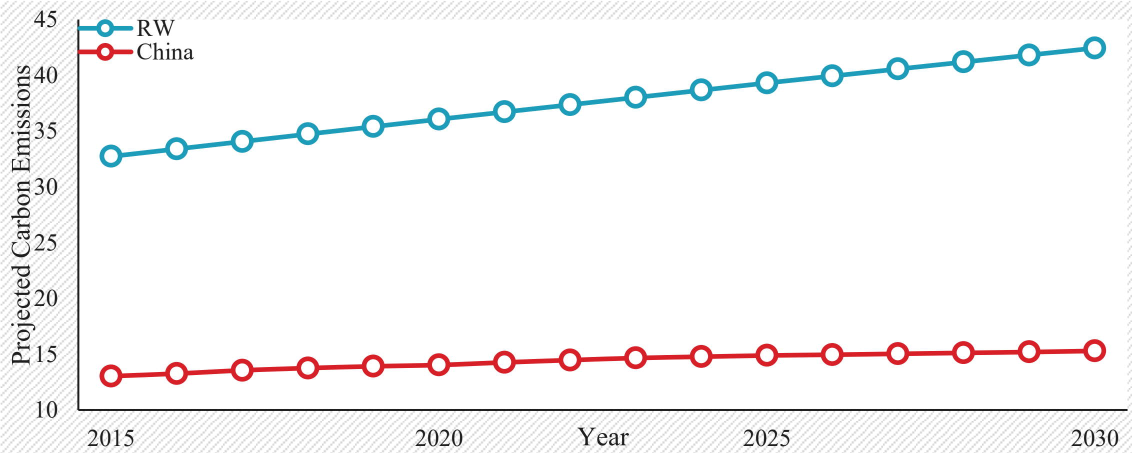


Fig. 3.1 The Projected Baseline Emissions in China and the Rest of the World (RW) (Unit: Gt)

Fig. 3.1 shows the projected China and RW emissions in the baseline scenario over the studied period. Fig. 3.1 implies that the baseline Chinese emissions are about one third of the RW emissions. The Chinese emissions will increase, but the increase rate will decline steadily over time. Similar findings can be found in the previous work by Yang and Teng (2018). By comparison, the RW emissions will increase drastically over the studied period, and the annual increase rate will remain relatively stable.

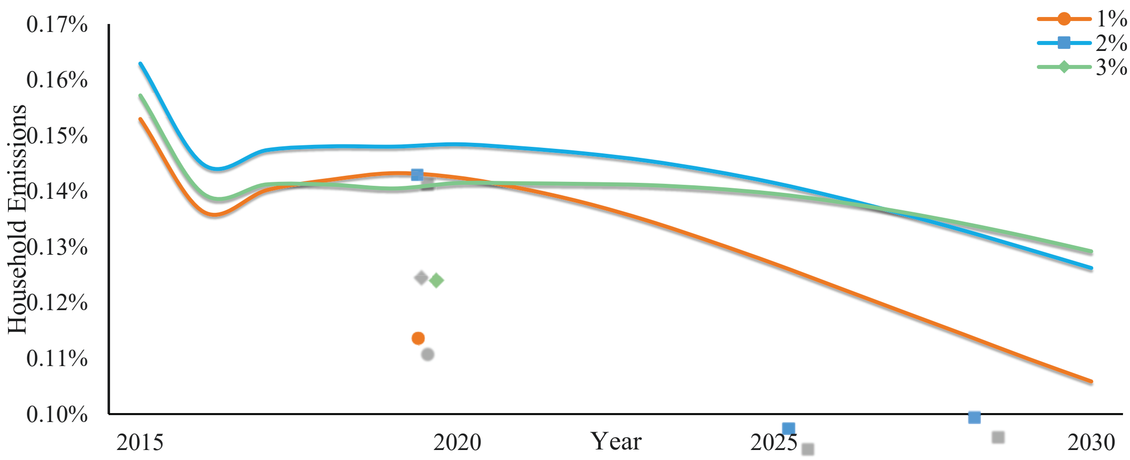


Fig. 3.2 The Relative Change of the Household Emissions Influenced by the Primary Benefit

Fig. 3.2 shows the impact of the primary benefit on the household emissions over the studied period. In all the tax scenarios, the primary benefit will increase the household emissions by 0.10%–0.17% even though its impact will fluctuate over time. The rationale underlying Fig. 3.2 is that the primary benefit improves the labour health (Anenberg, Henze et al. 2017), which increases the labour income (Boachie 2017) and thus the household welfare shown in Fig. 3.7. Hence, the primary benefit will increase the household energy consumption and carbon emissions.

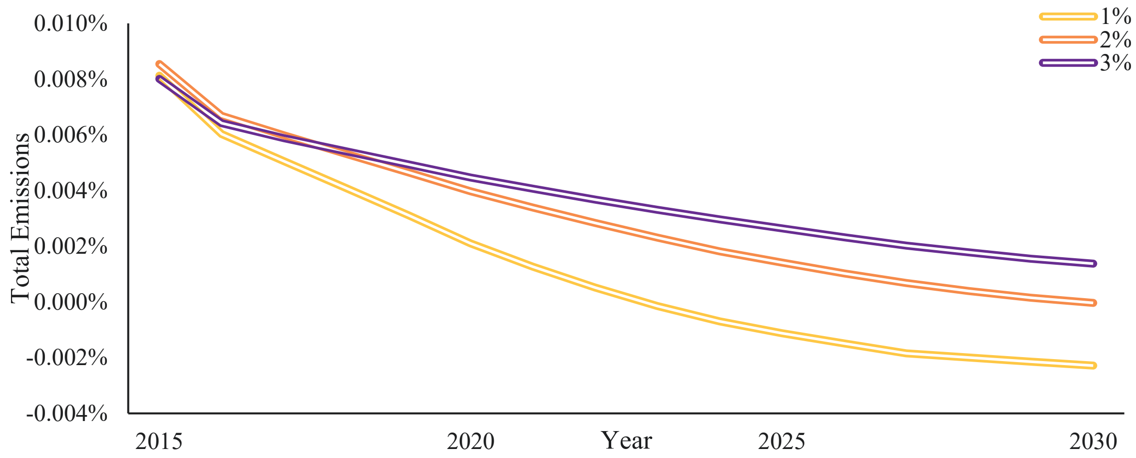


Fig. 3.3 The Relative Change of the Total Emissions Influenced by the Primary Benefit

Fig. 3.3 shows how the primary benefit of the carbon tax will affect the total emissions over the research period. According to Fig. 3.3, the primary benefit will have a decreasing impact on the total emissions over time, but the impact will increase as the tax rate rises. Fig. 3.3 implies that the primary benefit has a much smaller impact on the total emissions compared to the household emissions, which implies that the primary benefit is less distinct at the country level. In other words, the climate impact is not of vital importance to the analysis of the policy effect of the carbon tax on the emission reduction. This finding agrees with the previous research showing that the incentive to implementing the carbon tax is not a threat to mitigating the carbon emissions for the immediate future, according to Wang, Moreno-Cruz et al. (2017) who used the DICE model to check the incentives to continue carbon emissions.

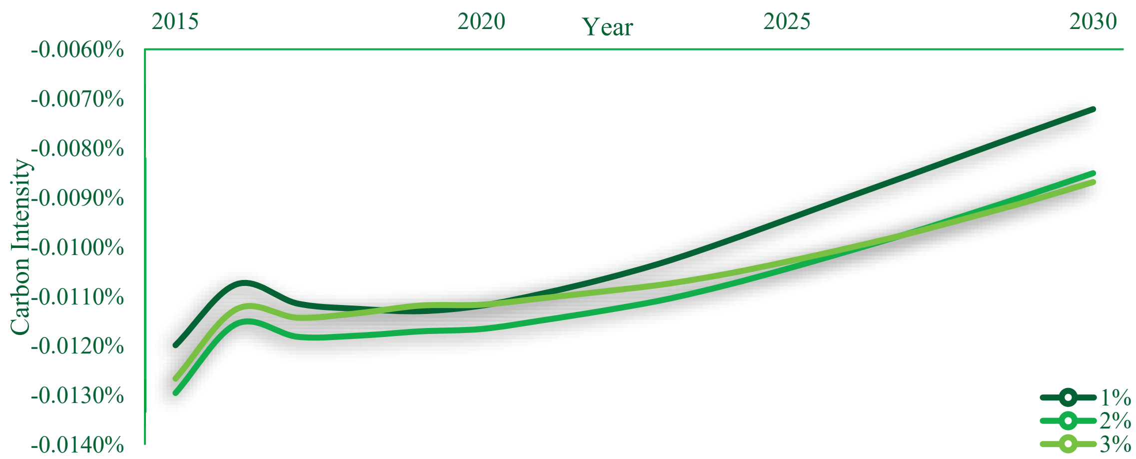


Fig. 3.4 The Relative Change of the Carbon Intensity Influenced by the Primary Benefit

Fig. 3.4 shows the variation of the carbon intensity under the primary benefit impact over the studied period. This impact fluctuated in 2015–2019 but will decrease gradually in 2020–2030. Generally, the primary benefit of the carbon tax will negatively influence the carbon intensity even though this impact is quite minimal. Fig. 3.4 implies that the primary benefit will increase the energy efficiency or the development of renewable energies to decrease the carbon intensity.

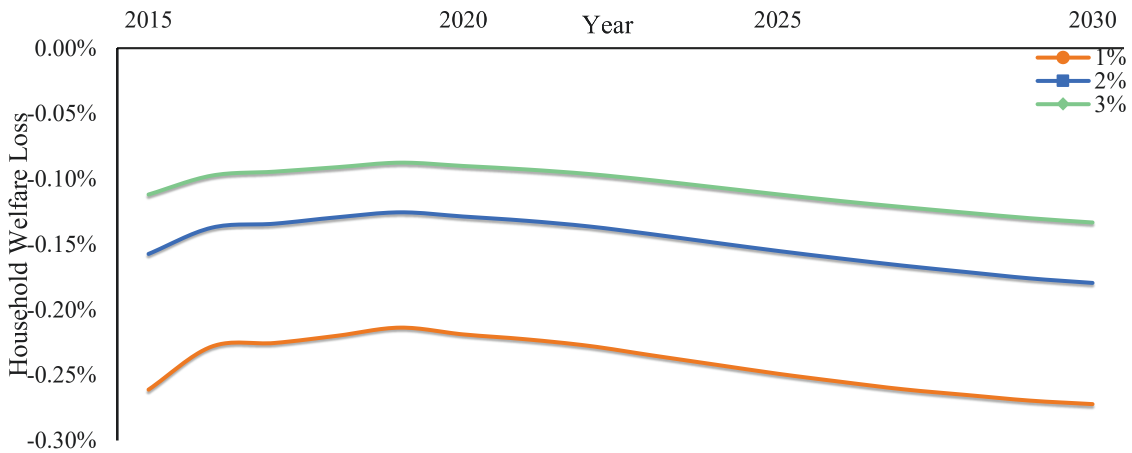


Fig. 3.5 The Relative Change of the Household Welfare Loss Influenced by the Primary Benefit

Fig. 3.5 shows the percentage change of the household welfare loss, denoted by the value of the Equivalent variation (EV), under the primary benefit impact over time. Fig. 3.5 implies that the primary benefit will decrease the household welfare loss, induced by the carbon tax, by 0.1%–0.3%. As the tax rate increases, this impact will be less distinct. The rationale underlying Fig. 3.5 is that the household is likely to suffer less from the extreme weather conditions and rising sea level when the primary benefit is considered. This finding agrees with the previous study concluding that the climate benefits would increase the household welfare, according to Freeman and Zerriffi (2012) who critically looked at the tradeoffs between the climate and health benefits of the cookstove projects.

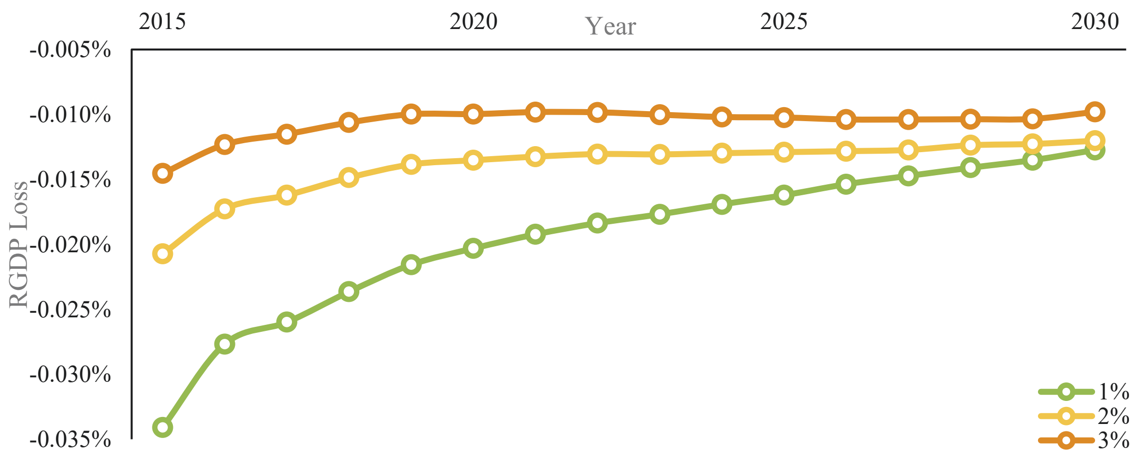


Fig. 3.6 The Relative Change of the RGDP Loss Influenced by the Primary Benefit

Fig. 3.6 shows how the primary benefit will affect the RGDP loss induced by the carbon tax over the studied period. This impact will decrease as the rate increases or the time goes by. Fig. 3.6 implies that the primary benefit of the carbon tax will decrease the RGDP loss and thus increase the real GDP, even though this impact is not distinct. The rationale underlying Fig. 3.6 is that the improved labour health, induced by the primary benefit, will increase the labour productivity and thus boost the economic growth. This finding consents to the previous study showing that the US carbon tax will result in an increase in the global social welfare when the benefits of reducing the emissions are included, according to Chen, Huang et al. (2014) who developed an integrated model of the fuel and agricultural sector.

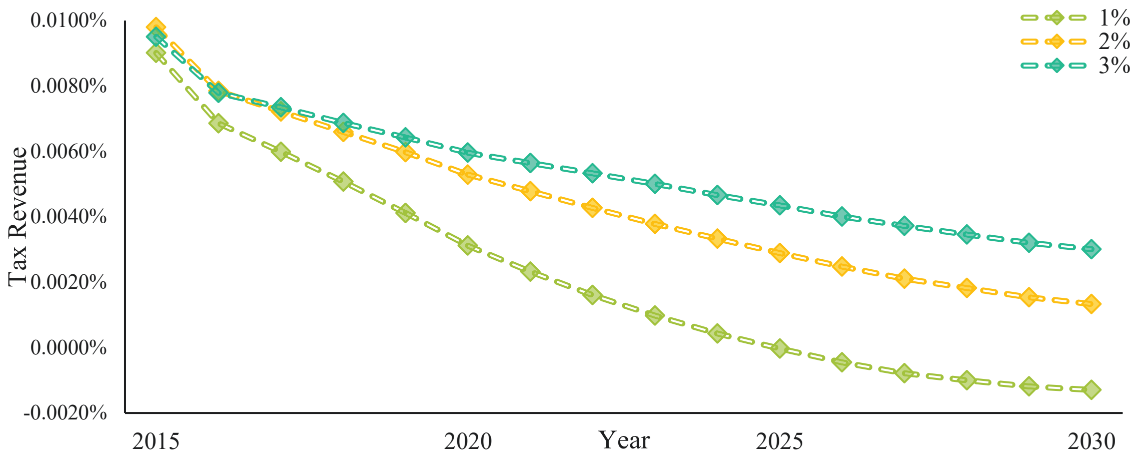


Fig. 3.7 The Relative Change of the Tax Revenues Influenced by the Primary Benefit

Fig. 3.7 shows the changes of the tax revenues when the primary benefit is considered. The primary benefit will have a very minimal impact on the tax revenues, and this impact will decrease over time. The curve for the 1% tax rate is larger than zero in 2015–2024, equal to zero in 2025, and less than zero in 2026–2030, whilst the primary benefit of the 1% and 2% tax will have positive impacts over the studied period. The positive impact of the primary benefit on the tax revenues can be attributed to the induced economic boom, shown in Fig. 3.6.

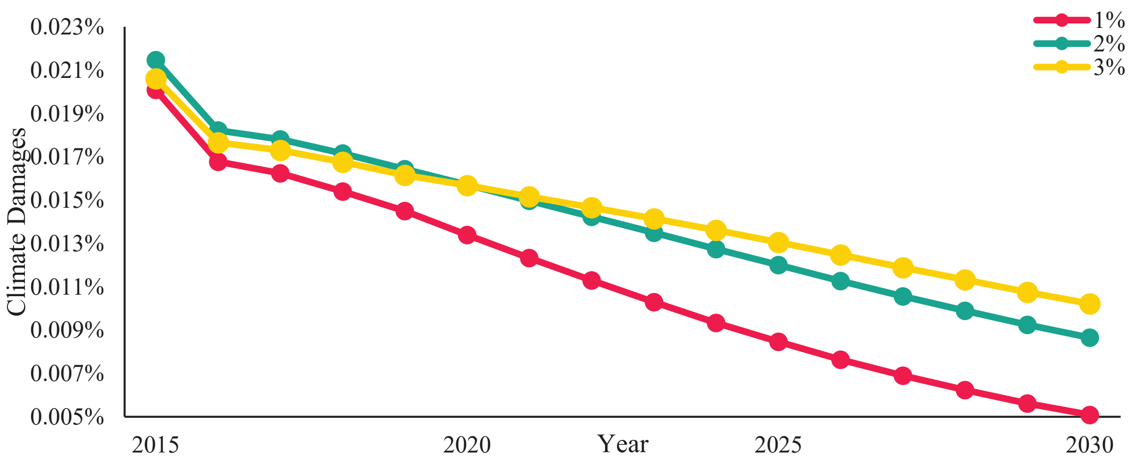


Fig. 3.8 The Relative Change of the Climate Damages Influenced by the Primary Benefit

Fig. 3.8 shows the variation of the climate damages under the primary benefit impact in the tax scenarios over time. The primary benefit will increase the monetary value of the climate damages. This impact is positively related to the tax rates but negatively rated to the time. Readers may expect that the primary benefit may decrease the climate damages because the primary benefits of climate policies are the avoided damages from the global warming (Lomborg 2020). However, Fig. 3.8 implies the opposite finding, owing to the projection that the primary benefit will generally increase the emissions, shown in Fig. 3.2 and 3.3. Hence, the primary benefit will have a promotion effect on the global warming and thus increase the climate damages.

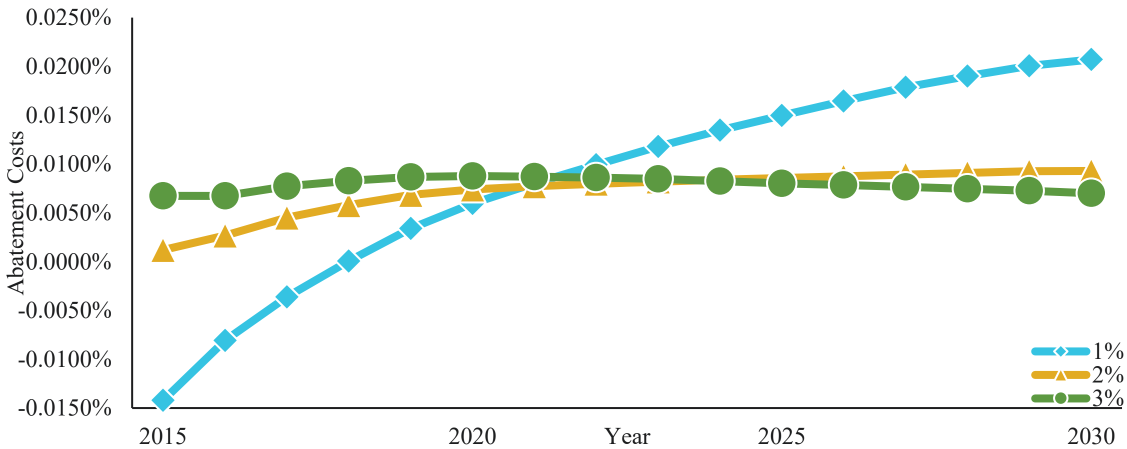
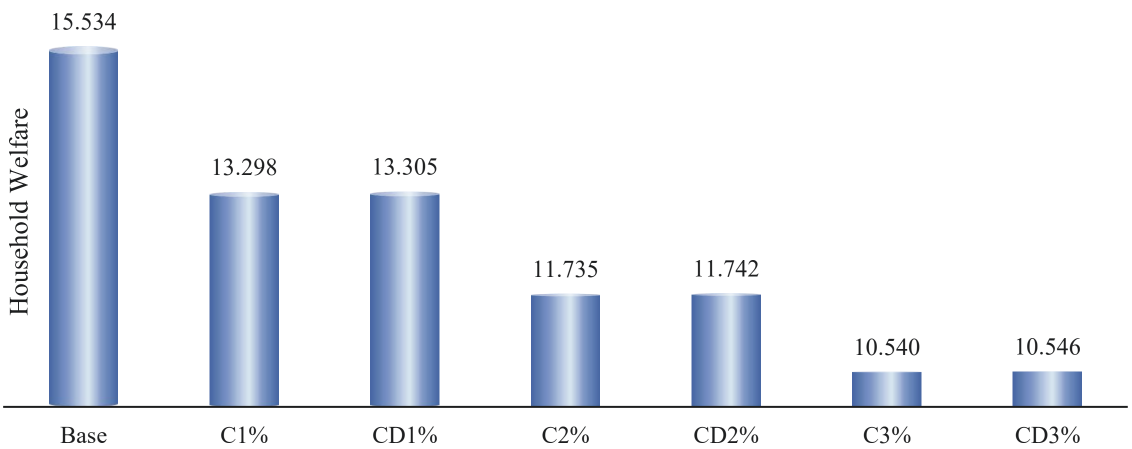


Fig. 3.9 The Relative Change of the Abatement Costs Influenced by the Primary Benefit

Fig. 3.9 shows the impact of the primary benefit on the abatement costs in the tax scenarios over time. This impact will increase steadily at the 1% tax but remain stable at the 2% and 3% tax. The primary benefit will have a very minimal impact and generally positively affect the abatement costs except that it decreased the costs in 2015–2019 at the 1% tax. The rationale underlying Fig. 3.9 is that the primary benefit will slightly increase the carbon emissions, shown in Fig. 3.2 and 3.3, and thus it is unfavorable to abate the emissions under the impact of the primary benefit.



Note: “C” and “CD” refers to the clean-air and CGE-DICE model respectively; “Base” refers to the baseline; “1%”, “2%”, “3%” refer to the tax rates.

Fig. 3.10 The Household Welfare Influenced by the Primary Benefit (Unit: 10^{18} CNY)

Fig. 3.10 shows the comparison of the household welfare between the clean-air and CGE-DICE model in three tax scenarios. In the baseline scenario, the household welfare is the same in the two models. In the tax scenarios, the primary benefit will have a slight and positive impact on the welfare. However, as the tax rate increases, the welfare will decrease regardless of the primary benefit, which implies that considering the primary benefit is not enough to change the social reluctance of the implementation of a climate policy. This finding complies with the previous research showing that the costs of climate policies usually outweighed the climate benefits, according to Lomborg (2020) who outlined how to establish a rational climate policy.

When the tax rate is endogenized, the results of the CGE-DICE model show that the optimum policy that incurs the largest household welfare is no tax imposed on any sector exploiting nonrenewable energy. The results imply that considering the primary and ancillary benefits are still not enough to make climate policies attractive to the government.

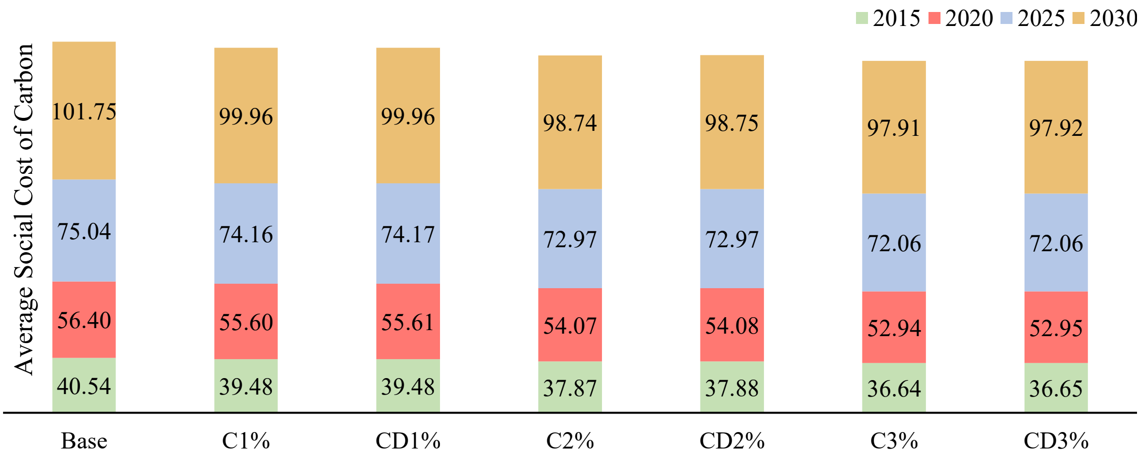
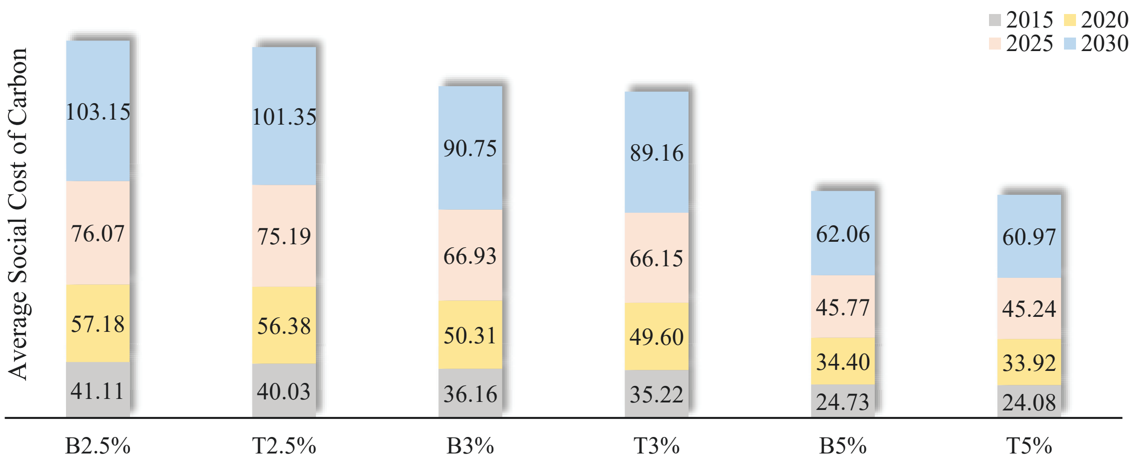


Fig. 3.11 The Comparison of the Average Social Cost of Carbon (ASCC) (Unit: 2015 $\$/t\ CO_2$)

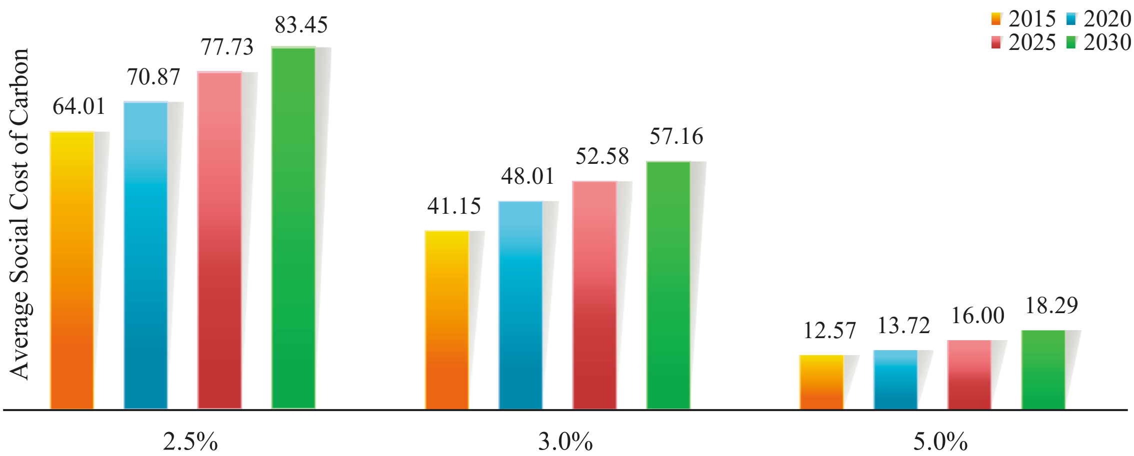
Fig. 3.11 shows the values of the ASCC in the clean-air and CGE-DICE model. In all the scenarios, the ASCC was projected to increase over the studied period. The carbon tax will decrease the ASCC, and the ASCC is negatively correlated with the tax rate. This is because the carbon tax will significantly decrease the carbon emissions, shown in Fig 1.9 and A1.4 in Appendix A. Nevertheless, the primary benefit of the tax will slightly increase the ASCC because it will slightly increase the carbon emissions, shown in Fig. 3.2 and 3.3. The baseline ASCC in 2015 is 40.54 $\$/t\ CO_2$ at $\sigma = 2.55\%$. The result in this chapter is in line with the previous research showing that the ASCC was 56.98 $\$/t\ CO_2$ at $\sigma = 2\%$ and 34.19 $\$/t\ CO_2$ at $\sigma = 3\%$, according to Tian, Ye et al. (2019) who used a simplified formula to calculate the ASCC in China.



Note: "B" and "T" refer to the baseline and 1% tax scenario respectively; "2.5%", "3%", and "5%" refer to the discount rate.

Fig. 3.12 The ASCC in China Influenced by the Social Discount Rate (Unit: 2015 $\$/t\ CO_2$)

Fig. 3.12 shows to what extent the social discount rate will affect the ASCC. According to Fig. 3.12, the ASCC will be negatively related to the discount rate in both the baseline and 1% tax scenario.



Data Source: EPA

Fig. 3.13 The ASCC in the US Influenced by the Social Discount Rate (Unit: 2015 $\$/t\ CO_2$)

Fig. 3.13 shows the ASCC in the US under the influence of the social discount rate according to The United States Environmental Protection Agency (EPA). When the discount rate is 2.5% or 3%, the ASCC in the US will be larger than that in China. Nevertheless, when the discount rate rises to 5%, China will unexpectedly have a higher ASCC. According to Ricke, Drouet et al. (2018) who estimated the country-level contributions to the SCC, the ASCC in China and the US was projected to be 24 and 48 $\$/t\ CO_2$ respectively in 2020, which implies that the discount rate in China and the US would be over 5% and approximately 3% respectively in 2020.

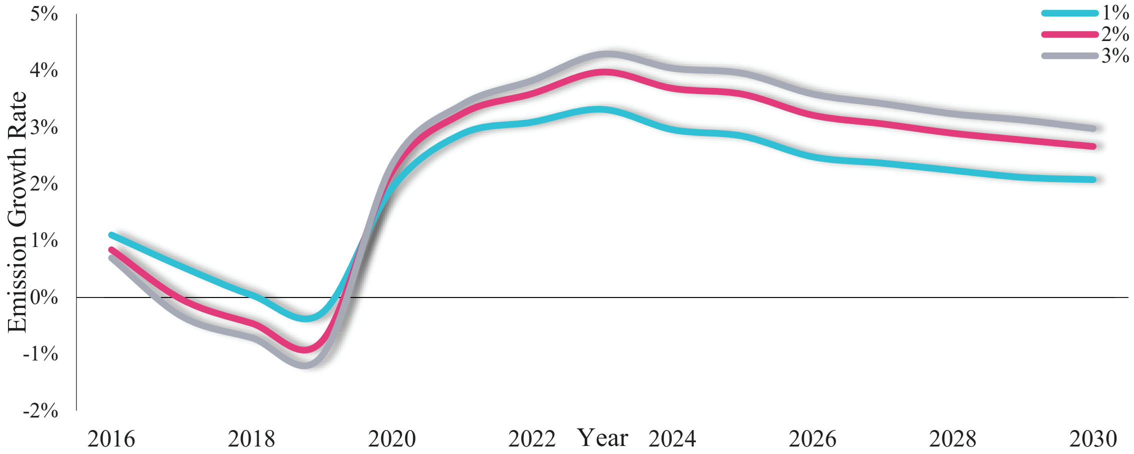


Fig. 3.14 The Projected Emission Growth Rate Influenced by the Primary Benefit

Fig. 3.14 shows the projected emission growth rate in the tax scenarios when the primary benefit is considered. As the emission growth rate in 2030 will be positive, China still cannot meet the INDC target of peaking the emissions in 2030 under the consideration of the primary benefit. Fig. 3.14 implies that China needs to take more measures in addition to the carbon tax to abate the emissions when both the ancillary and primary benefits of the carbon tax are considered. Nevertheless, as Fig. 3.4 shows the carbon intensity in the CGE-DICE model is even lower than that in the clean-air model defined in the previous chapter, China will meet the INDC target of the carbon intensity reduction in 2030.

Results of the Sensitivity Analysis

Table 3.3 The Changes of the Parametric Quintiles Relative to Q3

	Q1	Q2	Q4	Q5
KKdam	-74.15%	-40.25%	2.54%	96.61%
KKets	-35.24%	-18.84%	9.29%	44.88%
KKcarb	-35.11%	-18.63%	9.54%	44.26%

Table 3.3 shows the percentage changes of the quintiles based on Table 3.2. Table 3.3 implies that the value of KKdam will have a broader range than the other two parameters. Because the definitions of the emissions and welfare in this chapter are irrelated with KKdam, KKets, and KKcarb, the policy effects of the carbon tax on the emission reduction and welfare change are insensitive to these three parameters which form the geophysical equations in the DICE model. However, the values of the geophysical variables in this chapter need to be explored, as their definitions are closely related to these parameters.

Table 3.4 The Changes of the Atmospheric Temperature Increase Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2020	-4.68%	-1.54%	0.19%	0.17%	-4.59%	-1.49%	0.17%	0.08%
2025	-8.17%	-2.64%	0.18%	-1.32%	-7.97%	-2.52%	0.11%	-1.65%
2030	-11.79%	-4.31%	0.68%	-0.36%	-11.51%	-4.13%	0.58%	-0.89%

Table 3.4 shows how the atmospheric temperature increase is affected by the given geophysical parameters. According to Table 3.4, when the parametric values decrease from Q3 to Q1 or Q2, the

atmospheric temperature increase will decline both in the baseline and 1% tax scenario. Table 3.4 implies that the percentage changes of the temperature increase will be much smaller than the percentage changes of the parameters, which means that the geophysical parameters do not lay undue influences on this variable.

Table 3.5 The Changes of the Atmospheric Carbon Concentration Increase Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2020	12.96%	6.11%	-2.60%	-9.92%	13.04%	6.14%	-2.62%	-9.98%
2025	13.91%	6.78%	-3.04%	-12.13%	14.00%	6.83%	-3.06%	-12.22%
2030	13.98%	6.85%	-3.10%	-12.56%	14.06%	6.89%	-3.12%	-12.64%

Table 3.5 shows that the change of the atmospheric carbon concentration increase influenced by the exogenously given parametric values. According to Table 3.5, when the geophysical parameters increase from Q3 to Q4 or Q5, the carbon concentration increase will decline. Table 3.5 implies that the percentage changes of this variable will be also much smaller than the percentage changes of the geophysical parameters.

Table 3.6 The Changes of the Consumption Good Net Value Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	0.13%	0.07%	0.00%	-0.17%	0.13%	0.07%	0.00%	-0.17%
2020	0.37%	0.20%	-0.01%	-0.47%	0.36%	0.20%	-0.01%	-0.46%
2025	0.62%	0.34%	-0.02%	-0.72%	0.60%	0.33%	-0.02%	-0.69%
2030	0.87%	0.50%	-0.04%	-1.04%	0.84%	0.47%	-0.04%	-0.98%

Table 3.6 shows how the consumption goods, free from the climate damages and abatement costs, will change under the influence of the geophysical parameters. Table 3.6 implies that the net value of the consumption goods will vary slightly when the parameters change. This is because the abatements and damages take up only a small proportion of the overall consumption goods.

Table 3.7 The Changes of the Real Interest Rate Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	0.55%	0.32%	-0.04%	-0.82%	0.58%	0.33%	-0.04%	-0.86%
2020	0.61%	0.34%	-0.01%	-0.62%	0.50%	0.28%	-0.01%	-0.50%
2025	0.65%	0.38%	-0.04%	-0.74%	0.49%	0.28%	-0.03%	-0.53%
2029	0.67%	0.41%	-0.07%	-0.94%	0.53%	0.32%	-0.05%	-0.72%
2030	UND	UND	UND	UND	UND	UND	UND	UND

Note: “UND” stands for “undefined”.

Table 3.7 shows to what extent the parametric values will affect the real interest rate over time. Table 3.7 implies that the real interest rate is insensitive to the changes of the geophysical parameters. Noticeably, the real interest rate in 2030 is undefined as the geophysical equations in Nordhaus (2018) cannot calculate the value of this variable in the last year of the studied period.

Table 3.8 The Changes of the Damage Ratio Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	-74.15%	-40.25%	2.54%	96.61%	-74.15%	-40.25%	2.54%	96.61%
2020	-76.51%	-42.08%	2.93%	97.29%	-76.47%	-42.03%	2.88%	96.93%
2025	-78.21%	-43.37%	2.91%	91.44%	-78.11%	-43.22%	2.76%	90.18%
2030	-79.89%	-45.29%	3.95%	95.18%	-79.76%	-45.09%	3.73%	93.14%

Table 3.8 shows the influence of the geophysical parameters on the ratio of the climate damages to the output over the studied period. Table 3.8 implies that the damage ratio will change proportionally to the given parametric values. Specifically, the damage ratio is proportional to the damage parameter but insensitive to the other parameters.

Table 3.9 The Changes of the Household Welfare Quintiles Relative to Q3

Baseline Scenario				1% Tax Scenario			
Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
0.12%	0.07%	0.00%	-0.15%	0.17%	0.09%	-0.01%	-0.21%

Table 3.9 shows the variation of the household welfare influenced by the geophysical parameters over the research period. Table 3.9 implies that the household welfare is insensitive to the changes of the given values of the geophysical parameters.

Table 3.10 The Changes of the ASCC Quintiles Relative to Q3

	Baseline Scenario				1% Tax Scenario			
Year	Q1	Q2	Q4	Q5	Q1	Q2	Q4	Q5
2015	-74.23%	-40.33%	2.61%	96.78%	-74.23%	-40.33%	2.61%	96.78%
2020	-74.17%	-40.25%	2.60%	96.18%	-74.17%	-40.25%	2.60%	96.20%
2025	-74.11%	-40.16%	2.59%	95.68%	-74.11%	-40.17%	2.59%	95.74%
2030	-74.04%	-40.07%	2.57%	95.05%	-74.05%	-40.08%	2.57%	95.18%

Table 3.10 shows the variation of the average social cost of carbon (ASCC) quintiles under the influence of the geophysical parameters. The variation of the ASCC will remain stable over the research period. According to Table 3.10, the ASCC will have almost the same proportional changes to the damage parameter, implying that among the geophysical parameters, the damage parameter will have a crucial impact on the ASCC.

Table 3.11 The Social Discount Rate Defined in the DICE Model and This Chapter

Year	DICE	Eq. (3.17) in this Chapter			
Tax		0%	1%	2%	3%
2015	0	0.16	-0.53	-0.86	-1.05
2020	0.07	0.14	0.05	-0.05	-0.12
2025	0.14	0.13	0.05	-0.04	-0.10
2030	0.20	0.12	0.04	-0.06	-0.12

Table 3.11 shows the comparison of the social discount rate between the DICE model and this chapter. The social discount rate r_t in the DICE model will increase drastically as the time goes by. By comparison, r_t will remain relatively stable in the baseline scenario of this chapter. In the 1% tax scenario, r_t was negative in 2015 but will remain positive in 2016–2030. This is because the carbon tax decreased the energy consumption in 2015, but no tax was imposed in 2014. The social discount rate will become negative when the economic growth in the current year is less than that in the previous

year. This is the case at the 2% or 3% tax where the economic growth rate and thus the social discount rate will be negative over the studied period.

Table 3.12 The Household Welfare Influenced by the Social Discount Rate (Unit: 10^{18} CNY)

Tax	0%	1%	2%	3%
Using r_t in DICE Model	15.53	13.30	11.74	10.55
Using r_t in Eq. (3.17)	15.13	14.78	14.46	13.83

Table 3.12 shows the impacts of the social discount rate on the household welfare in the baseline and tax scenarios. Table 3.12 implies that using r_t in this chapter instead of the DICE model will decrease the welfare in the baseline scenario but increase the welfare in the tax scenarios. Irrespective of the value of r_t, the carbon tax will decrease the household welfare with the impact increasing as the tax rate increases.

Table 3.13 The Household Welfare Influenced by η (Unit: 10^{18} CNY)

Tax	0%	1%	2%	3%
$\eta = 3$	-10.25	-10.26	-10.29	-10.32
$\eta = 2$	-0.65	-1.05	-1.39	-1.69
$\eta = 1.5$	13.29	11.38	10.03	8.97
$\eta = 1.45$	15.53	13.30	11.74	10.55
$\eta = 1$	51.40	42.00	36.41	32.55
$\eta = 2/3$	117.37	89.53	74.84	65.43

Table 3.13 shows the changes of the household welfare influenced by the inequality parameter (η) in the baseline and tax scenarios. As the value of η decreases, the household welfare will increase dramatically. Interestingly, when η equals 2 or 3, the household welfare will become negative, implying that the inequality parameter severely affects the household welfare. In addition, the large variation of the welfare under the influence of the inequality parameter suggests that the definition of the welfare function in the DICE model is susceptible to the exogenous values of the inequality parameter, and thus it needs to be improved.

Table 3.14 The Household Welfare Influenced by δ (Unit: 10^{18} CNY)

Tax	0%	1%	2%	3%
$\delta = 0$	17.45	15.01	13.30	11.99
$\delta = 0.001$	17.31	14.89	13.19	11.89
$\delta = 0.015$	15.53	13.30	11.74	10.55
$\delta = 0.02$	14.96	12.80	11.28	10.12

Table 3.14 shows how the household welfare will vary under the influence of the pure time preference rate (δ). Generally, the value of δ will be negatively correlated with the household welfare over time: a lower δ value will induce the higher welfare, whilst a higher δ value will induce the lower welfare. As the δ value only slightly affects the household welfare, I conclude that the household welfare is robust to the uncertainties of δ. This is because the time preference indirectly affects the welfare, and this indirect effect is moderated by the social discount rate.

Discussion

This chapter empirically shows that the primary benefit will reduce the carbon intensity. The reduction of the intensity denotes the energy efficiency improvement, which saves the energy consumption and thus will generate the climate benefits (Trotta 2019). Trotta (2020) and Buonocore, Luckow et al. (2016) also drew similar conclusions. Hence, a bidirectional link exists between the climate benefit and intensity. On the contrary, Lankoski and Ollikainen (2011) developed a general economic–ecological modelling framework and empirically found that the climate benefit did not promote the biofuels production under the current technology. Hence, the impact of the climate benefit on reducing the carbon intensity must be accompanied by the enhanced technological innovation (Irandoust 2019). Only an adoption of a new technique that saved energy consumption would induce the climate benefits, according to Saliba, Subramanian et al. (2018) who measured optical properties of fresh aerosol emissions from stoves. Hence, the minimal impact of the primary benefit on the carbon intensity in this chapter agrees with the findings in Lankoski and Ollikainen (2011), Irandoust (2019), and Saliba, Subramanian et al. (2018).

The primary benefit will significantly decrease the deadweight loss of the carbon tax and thus increase the output, especially for the agriculture sector whose output is severely affected by the climate change. For example, Sathre and Gustavsson (2009) developed a bottom-up method to empirically show that the climate benefit of the carbon tax significantly increased the added values of the forest product industries. As for the representative household, the primary benefit will also increase the welfare. Since the accelerating global warming will cause the severe economic costs and reduce the welfare (Vousdoukas, Mentaschi et al. 2017, Jevrejeva, Jackson et al. 2018), climate policies that relieve the global warming will generate the economic and welfare benefits.

The primary benefit will increase the tax revenues. This finding agrees with Wang, Moreno-Cruz et al. (2017) who used the DICE model to demonstrate that the carbon tax for revenue generation could potentially motivate the tax implementation today, but this source of the revenue generation would start to risk motivating the continued carbon emissions in 2085. As the research period in this chapter only extends to 2030, the primary benefit will generally increase the tax revenues over time.

The primary benefit of the carbon tax will increase the climate damages because it will increase the emissions and thus exacerbate the climate change. According to Lontzek, Cai et al. (2015) who used a stochastic integrated assessment model to indicate the need for a strict climate policy, the irreversible impacts of the tipping events, pushed by human activities, would increase with the global warming. In addition, the primary benefit of the Chinese carbon tax could have a global impact but only the regional impact is modelled in this chapter. This is because the climate is a kind of public goods owing to its nonexcludable and nonrivalry features. A previous study on the US climate policy concluded that the US policy resulted in a net cooling on a global scale, but the policy led to a net positive forcing over the USA on a regional scale, implied by the NASA GISS ModelE2 general circulation model (Lee, Shindell et al. 2016).

The primary benefit will minimally affect the abatement costs, and the impact is positive in most cases. This finding corresponds to the fact that in the developing countries, primary benefits play a minor role on the political agenda (Rubbelke 2006). This is because challenges existed in undertaking assessments of climate policies, according to Cohen, Tyler et al. (2017) who did co-impacts assessment under the Mitigation Action Plans and Scenarios (MAPS) Programme. Hence, the overwhelming near-term development priorities in the developing countries impair the promotion of the climate benefits on the reduction of the abatement costs. In contrast, climate benefits are more concerned in the developed countries. For example, Woollacott (2018) used the forward-looking dynamic CGE model to identify the required amount of the climate benefits to justify the emission abatement achieved by the carbon tax in the US. Similarly, Melvin, Sarofim et al. (2016) monetised the climate and ozone-health impacts of the methane reductions and concluded that the US EPA policies generated the climate and air quality benefits.

In summary, the main contribution of this chapter is the introduction of the primary benefits, using the geophysical equations of the DICE/RICE models, to the CGE framework in analysing the policy effects of the carbon tax. Future researchers could introduce other types of the IAMs to the CGE framework. This is because the ancillary benefits of climate policies, quantified by CGE models or other socioeconomic models, can be comparable in size to the primary benefits, modelled by the IAMs, according to Pearce (2000).

The sensitivity analysis shows that among all the geophysical parameters, only the damage parameter will place undue influences on the climate damages over the studied period. This finding implies that all the geophysical variables, except for the damage variable, are insensitive to the given parametric values and perform well in the CGE-DICE model. The sensitivity of the damage parameter corresponds to the argument that the damage functions in the IAMs simply reflect the common beliefs, but they are completely made up with no theoretical or empirical foundation (Pindyck 2013). Moreover, the measurement of the household welfare is insensitive to the given parametric values of the discount rate and pure time preference rate, but it is subject to the variations of the inequality parameter. This finding implies that the intergenerational inequality will severely affect the household welfare over time.

Hence, future potential research may lie in a clear clarification of the damage function, whose result should be insensitive to the exogenous values of the damage parameter. The quantification of the household welfare also needs to be improved in a way that its value should not be susceptible to the given value of the inequality parameter. Only when the undue influences from all the exogenous parameters are excluded will the authentic impacts of the primary benefit be modelled in the CGE-DICE model.

Another potential research lies in the clear modelling of the global primary benefits of the Chinese carbon tax. The climate benefits usually extend beyond the local region where the climate policy is implemented (Lee, Shindell et al. 2016). As this chapter only focuses on the regional primary benefit of the Chinese carbon tax, the results tend to underestimate the entire primary benefits of the tax.

According to the Tinbergen Rule (Tinbergen 1952), there must be at least one policy instrument for each policy target; in other words, when instruments are fewer than targets, then some targets will not be achieved (Knudson 2009). Hence, the primary benefits, quantified in this chapter, may not be the largest when the carbon tax is simulated to achieve the ancillary benefit defined in the last chapter. To achieve the largest primary benefit, a unique policy instrument, like reforestation, needs to be implemented.

Policy Implications

Considering the primary benefit will weaken the policy effects of the carbon tax on the emission reduction and welfare loss, but it will strengthen the policy effects on the intensity reduction. When the primary benefit is considered, the carbon tax will not help China meet the INDC target of peaking the emissions.

Conclusion

The empirical research in this chapter found that the primary benefit will increase the household emissions by 0.10%–0.17% owing to the induced improvement of the labour health. Nevertheless, the primary benefit will decrease the carbon intensity by approximately 0.01% because the primary benefit will induce the economic boom and energy efficiency improvement. The primary benefit will decrease the household welfare loss, induced by the carbon tax, by 0.1%–0.3%. This is because the labour health improvement will increase the labour income and thus household welfare.

The carbon tax will decrease the average social cost of carbon (ASCC) because of the negative policy effects of the tax on the carbon emissions. Nevertheless, the primary benefit will minimally increase the ASCC in the tax scenarios because it will increase the emissions. A higher value of the social discount rate will induce a lower value of the ASCC. The sensitivity analysis shows that among all the geophysical parameters, only the damage parameter will severely affect the values of the geophysical variable, namely the ratio of the climate damages to the output. The household welfare will vary dramatically if the inequality parameter changes, implying that the definition of the welfare function in the DICE model needs improving. Considering the primary benefit of the tax is still not enough to help China meet the INDC target of peaking its emissions in 2030.

Chapter 4: The Technical Impacts of the Carbon Tax

Introduction

To address the challenges aroused by the accelerating global warming, the United Nations Environmental Program calls upon global action to adopt mitigation technologies to control the anthropogenic emissions and limit the global temperature rise (Wang, Li et al. 2018). The United Nation Framework Convention on Climate Change (UNFCCC) emphasises that technological transfer should be an important element in global action to mitigate the climate change. This is because technology is at the root of the climate change as well as an integral part of the mitigation process (Akhavan and Jabbari 2007).

Despite the significant role of technology in relieving the global warming, technology was usually treated as an exogenous variable in the previous studies on designing climate policies (Popp 2004). The omission of the technological impacts is likely to overestimate the economic costs of climate policies. This is because the technological progress can lower the cost of reducing carbon emissions over time, according to Fried (2018) who used a dynamic general equilibrium model with the endogenization of energy inputs. Indeed, switching from dirty energy production technologies to clean energy production technologies has become a possible answer to today's environmental problems (Tang, Zhong et al. 2019). Hence, it is important to endogenously model the technical impacts as the assumptions on the technological change have significant impacts on the evaluation of climate policies (Baker and Shittu 2008).

Previously, the endogenization of technology has already become popular to address the issues relating to the climate change (Goulder and Schneider 1999, Goulder and Mathai 2000, van der Zwaan, Gerlagh et al. 2002). Researchers tend to use the induced technological change (ITC) to denote the technical impacts in empirical analyses. With the ITC included, the climate policies could meet the abatement target more easily than the policies without the ITC impacts, according to van der Zwaan, Gerlagh et al. (2002) who employed a macroeconomic model to study how the endogenous technological change affected the emission abatement and tax levels . This is because the ITC warrants earlier investments in the non-fossil carbon-free technology (van der Zwaan, Gerlagh et al. 2002) and thus promotes the development of renewable energies. Therefore, the inclusion of the ITC in modelling the climate issues tends to reduce the costs of climate policies and lead to positive spillover and negative leakage (Loschel 2002).

Although many previous researchers modelled how technology policies promoted technical progress to abate carbon emissions (Hanson and Laitner 2006, Wang, Mao et al. 2018), very few studies have focused on the ITC impacts of climate policies. As the carbon pricing in climate policies may crowd out intrinsic motivations and voluntary action to reduce emissions (van den Bergh 2013), the ITC impacts could be very different in climate policies from technology policies. For example, although the carbon pricing increased the quantity and proportion of the clean invention patents, its effect on the overall R&D was negative, according to Lin, Wang et al. (2018) who employed a counter-factual method to estimate the impact of the Chinese carbon market on the innovation of clean technology. In addition to the negative impacts on technical progress, there is a negative feedback of the ITC induced by climate policies. According to Sorrell, Dimitropoulos et al. (2009) who focused entirely on household energy services, this feedback is called "direct rebound effect": a promotion of the green technology to replace the carbon fuels decreases the carbon price, and thus the fossil fuels will become more attractive and be used more, which erases some of the stimulus provided by the ITC (Folster and Nystrom 2010).

Considering the complicated ITC impacts, whether climate policies will promote or inhibit technical progress remain to be researched. Previously, Gans (2012) examined whether climate policies would induce innovation in environmentally friendly technologies or crowding out the intrinsic innovation in the economy, concluding that only technologies directly abating carbon emissions would have an unambiguously positive impact on technical innovation. However, Gans (2012) only designed a single-sector mathematic model, which may not conform to the multi-sector reality. Hence, it is desirable that a multi-sector model is designed to assess the net policy effects of the carbon pricing on the technical progress.

When researchers model the ITC impacts of climate policies, CGE models have many advantages, including the ability to study both national and sectoral mitigation policies, according to Jacoby, Reilly et al. (2006) who used the MIT Emissions Prediction and Policy Analysis model to analyse the impact of potential technical change on the projection of emissions and mitigation costs. However, these advantages come at a price. For example, substantial uncertainties exist in all the variables reflecting a technical process, and the residuals yet remain to be poorly understood (Jacoby, Reilly et al. 2006). Uncertainties also apply to the modelling and analysis of the nonextant technologies, such as the wind and solar power for electricity generation (Jacoby, Reilly et al. 2006).

In this chapter, the empirical model that captures the ITC impacts is built on the CGE-DICE model developed in the previous chapter. Specifically, a technical block is added to the CGE framework, and thus the developed model in this chapter is called the technical model. This chapter contributes to the literature mainly by including the ITC impacts of climate policies in addition to the ancillary and primary benefits discussed in the previous chapters. To my best knowledge, no previous research has been performed to collectively model all the three influential factors of climate policies. Hence, the model results of this chapter will answer whether the designed carbon tax will help China meet the INDC target in 2030 more persuasively.

Method

To model the ITC impacts of the carbon tax, this chapter mainly refers to the quantification method in Wang, Saunders et al. (2019) who studied the relation between efficiency changes and energy cost share. In other words, the ITC impacts are denoted by the changes of the energy and nonenergy efficiencies if the carbon tax changes the energy cost share. In the reality, the efficiency changes can be achieved by the R&D investment, which is influenced by the scale effect. For example, if the carbon tax increases the consumption costs of nonrenewable energy, the nonrenewable energy production will become less attractive, and thus resources will be shifted away from nonrenewable energy sectors. Consequently, the R&D investment in nonrenewable energy sectors will decrease, and thus the energy production efficiency will also decrease. Noticeable, the ITC impacts in Wang, Saunders et al. (2019) mainly included the potential changes of the energy-saving technologies, but they excluded the induced development of the decarbonisation or clean energies. Hence, the ITC quantified in this chapter may underestimate the technical impacts in the real world.

There are major differences in the embedded assumptions of the energy price and technical index between Wang, Saunders et al. (2019) and this chapter. Wang, Saunders et al. (2019) endogenously determined the energy price, but the future technical index was determined by the historical data using simple loglinear functions. However, in this chapter, the energy price is exogenously determined according to OECD (2014), but the future technical index is endogenously determined in the CGE model.

The economy is assumed to be in a semi-steady state of capital allocation where the capital is allocated to maximise the output, but the capital stock will change because of the annual capital accumulation. According to Wang, Saunders et al. (2019), the real GDP (RGDP) can be expressed as a constant-elasticity-of-substitution (CES) production function of the energy and nonenergy goods, shown in Eq. (4.1). $NONEN_t$ refers to the nonenergy goods in Year t; EUE_t denotes the energy-use efficiency in Year t; $T\ddot{E}C_t$ is the total adjusted energy consumption in Year t. The reason to adjust the energy consumption is that the different energies have different units, and thus it is meaningless to make the summation directly. σ_{en} is the elasticity of substitution between the energy and nonenergy goods, and its centralised value is 0.4 according to Wang, Saunders et al. (2019). In Eq. (4.1), the nonenergy-use efficiency is assumed to be one.

$$RGDP_t = \left[\left(EUE_t \times T\ddot{E}C_t \right)^{\frac{\sigma_{en}-1}{\sigma_{en}}} + NONEN_t^{\frac{\sigma_{en}-1}{\sigma_{en}}} \right]^{\frac{\sigma_{en}}{\sigma_{en}-1}} \tag{4.1}$$

The energy cost share is defined in Eq. (4.2), where EC_{iqt} refers to the consumption of Energy q in Sector i in Year t; ECS_t stands for the total energy cost share in Year t. In this chapter, each sector is assumed to produce only one type of goods, which implies that an energy sector only produces one type of energy goods, and a nonenergy sector produces one type of nonenergy goods.

$$ECS_t = \frac{\sum_i \sum_q (PE_{iqt} \times EC_{iqt})}{RGDP_t} \tag{4.2}$$

In Eq. (4.2), PE_{iqt} denotes the absolute energy price of Energy q in Sector i in Year t, and this variable is used to transform the physical amounts of the energy consumption into the monetary values. Noticeably, the energy price in Wang, Saunders et al. (2019) is endogenously determined, whilst in this chapter, the predicted energy price over time is exogenously given for the sake of the conformity of the CGE-DICE model. The energy price data in 2015–2018 are from the online open source (shown in Table 4.1–4.4 in the Data Section of this chapter), but the predicted data for 2019–2030 is currently unavailable. Hence, the future energy price, except for the electricity price, is assumed to change proportionally to the 2018 energy price based on the predicted price change by OECD (2014). The 2020–2030 electricity price is assumed to change proportionally to the 2019 electricity price according to OECD (2014).

Based on the calculation of the ECS, the energy-use efficiency (EUE) is defined in Eq. (4.3). This EUE definition is different from Wang, Saunders et al. (2019) who defined the EUE based on the historical data. In Eq. (4.3), the exponent is always negative because the elasticity parameter σ_{en} is always less than one. Hence, the EUE is negatively correlated with the ECS, and thus the increase of the ECS will decrease the EUE. In contrast, Wang, Saunders et al. (2019) defined the EUE as a loglinear function of the ECS with a positive slope.

$$EUE_t = ECS_t^{\frac{\sigma_{en}-1}{\sigma_{en}}} \times \frac{RGDP_t}{T\ddot{E}C_t} \tag{4.3}$$

$$T\ddot{E}C_t = \sum_i \sum_q (EC_{iqt} \times Conv_q) \tag{4.4}$$

In Eq. (4.3), $T\ddot{E}C_t$ refers to the total adjusted energy consumption in Year t, and its unit is a tonne of standard coal. Different from Wang, Saunders et al. (2019), annual sectoral energy consumption data are used in this chapter. To get the annual sectoral overall energy consumption data, in this chapter, sectoral energy consumption is converted into the unit of standard coal before the summation. Hence, the value of $T\ddot{E}C_t$ is calculated using Eq. (4.4) where $Conv_q$ refers to the conversion coefficient of Energy q to the standard coal (Scoal). The energy conversion coefficient data are obtained from 2016 China Statistical Yearbook by NBS (2016) and compiled in Table 4.5 in the Data Section of this chapter.

Wang, Saunders et al. (2019) implicitly assumed that the quantities of the consumption goods are equal to the quantities of the production goods, which implies that the consumption of the imported goods is equal to the production of the export goods. In the reality, this assumption is seldom met because there are always net exporters or importers in the open economy. Hence, in this chapter, this assumption has been relaxed, and I assume that the energy cost share in the consumption goods is equal to that in the production goods.

Eq. (4.5) and (4.6) define the physical amounts of the energy and nonenergy production goods respectively. The subscript e and ne denote an energy sector and nonenergy sector respectively. QM_{it} is the import of Sector i in Year t; QE_{it} is the export of Sector i in Year t. $TEPC_t$ is the total energy production goods in Year t; $NONEP_t$ is the total nonenergy production goods in Year t. $NONEN_t$ refers to the nonenergy consumption goods, and Eq. (4.7) is derived from Eq. (4.1).

$$\frac{TEPC_t}{T\ddot{E}C_t} = \frac{\sum_e SGDP_{et}}{\sum_e SGDP_{et} + \sum_e QM_{et} - \sum_e QE_{et}} \tag{4.5}$$

$$\frac{NONEP_t}{NONEN_t} = \frac{\sum_{ne} SGDP_{ne,t}}{\sum_{ne} SGDP_{ne,t} + \sum_{ne} QM_{ne,t} - \sum_{ne} QE_{ne,t}} \tag{4.6}$$

$$NONEN_t = \left[RGDP_t^{\frac{\sigma_{en}-1}{\sigma_{en}}} - \left(EUE_t \times T\ddot{E}C_t\right)^{\frac{\sigma_{en}-1}{\sigma_{en}}}\right]^{\frac{\sigma_{en}}{\sigma_{en}-1}} \tag{4.7}$$

When the production goods are calculated using Eq. (4.5) and (4.6), Eq. (4.8) and (4.9) denote the definition of the energy-production efficiency (EPE) and nonenergy-production efficiency (ENE) respectively. In Eq. (4.8) and (4.9), the physical amounts of the production and consumption goods are assumed to be proportional to their monetary values. As the sectoral ECS is undefined in this chapter, the sectoral EPE and ENE are also undefined, implying that the EPE and ENE in all the sectors are equal to the national level. Hence, the definitions of the EPE and ENE in this chapter are quite different from Wang, Saunders et al. (2019) who calculated the EUE and EPE using the historical data, assuming that there was a loglinear relationship between the ECS and EUE or between the ECS and EPE. Based on the definitions of the EUE [defined in Eq. (4.3)], EPE and ENE, the technic index is defined in Eq. (4.10), according to Wang, Saunders et al. (2019). ATC_t refers to the technical index in Year t.

$$EPE_t = \frac{TEPC_t}{RGDP_t \times ECS_t} = \frac{T\ddot{E}C_t}{RGDP_t \times ECS_t} \times \frac{\sum_e SGDP_{et}}{\sum_e SGDP_{et} + \sum_e QM_{et} - \sum_e QE_{et}} \tag{4.8}$$

$$ENE_t = \frac{NONEP_t}{RGDP_t \times (1 - ECS_t)} = \frac{NONEN_t}{RGDP_t \times (1 - ECS_t)} \times \frac{\sum_{ne} SGDP_{ne,t}}{\sum_{ne} SGDP_{ne,t} + \sum_{ne} QM_{ne,t} - \sum_{ne} QE_{ne,t}} \tag{4.9}$$

$$ATC_t = \left[(EUE_t \times EPE_t)^{\sigma_{en}-1} + ENE_t^{\sigma_{en}-1}\right]^{\frac{1}{\sigma_{en}-1}} \tag{4.10}$$

The carbon tax changes the ECS and thus will affect the marginal benefits to improve the EUE, EPE, and ENE. Compared to the definition of the ECS in the baseline scenario shown in Eq. (4.2), the ECS in the tax scenarios is defined in Eq. (4.11), where the superscript * stands for the tax scenarios. Λ_t refers to the abatement costs in Year t, and its value is calculated using Eq. (4.12). $\theta_{1t} = 0.0741 \times 0.0904^{t-1}$ and $\theta_2 = 2.6$ are from the DICE model by Nordhaus (2018). μ_t is the proportion of the reduced emissions, and its value is zero in the baseline scenario. In this chapter, the dispersion of the sectoral abatement costs to the total costs are assumed to be the same as that of the sectoral emissions to the total emissions. Because of the abatement costs, the ECS in the tax scenarios is always larger than that in the baseline scenario.

$$ECS_t^* = \frac{\sum_i \sum_q (PE_{iqt} \times EC_{iqt}^*) + \Lambda_t}{RGDP_t^*} \tag{4.11}$$

$$\Lambda_t = \theta_{1t} \times {\mu_t}^{\theta_2} \tag{4.12}$$

The internalisation of the abatement costs increases the costs of the energy consumption. Wang, Saunders et al. (2019) argued that increasing the energy costs may induce more rapid technological change, because the increasing costs could accelerate the development of renewable energy and induce the energy-saving efficiency improvements. Nevertheless, Wang, Saunders et al. (2019) neglected the negative impacts of the increasing costs on the technical progress. Because the energy goods become more expensive after the tax is imposed, more resources will be shifted to the consumption and production of the nonenergy goods. The impacts of this resource shift cannot be modelled in Wang, Saunders et al. (2019). In contrast, the resource shift can be modelled in the CGE part of this chapter: as more resources will be shifted to the nonenergy sectors, confronted with less resources, the energy sectors will spend less funds on the R&D, and thus the EUE and EPE will decrease. Hence, a change in the energy cost share will finally induce a variation of the technical index.

In this chapter, the real GDP (RGDP) is defined as the summation of the added-values of the sectoral household income, capital income, and net production tax according to 2015 China Input-Output Table by NBS (2015). The Solow–Swan Growth model (Solow 1956) implies that the technology affects the economic growth. Hence, the technical impact on the RGDP is defined in Eq. (4.13), where the superscript 0 denotes the baseline scenario. YH_{it}^*, YK_{it}^*, and $GINDTAX_{it}^*$ stand for the labour income, capital income, and net production tax in the tax scenarios. Noticeably, in this chapter, the costs of the resource shifting among the sectors, induced by the carbon tax, are assumed to be zero. In the reality, the existence of the transaction costs may reduce the technical benefits of the carbon tax.

$$RGDP_t^* = \sum_i (YH_{it}^* + YK_{it}^* + GINDTAX_{it}^*) \times ATC_t^* / ATC_t^0 \tag{4.13}$$

To analyse how the ITC affects the model equilibrium, I compare the results of the technical (TL) model, defined in this chapter, with the results of the CGE-DICE (CD) model, defined in the previous chapter. The main differences between the two models lie in Eq. (4.11) and (4.13): the technical model has internalised the abatement costs as a part of the energy cost share, which affects the EUE, EPE, and ENE. These three indexes are directly linked to the definition of the technical index and thus the RGDP. In the baseline scenario, there are no differences in the socioeconomic conditions simulated by the two models; however, the carbon tax will change the equilibrium, and the consideration of the technical impacts will influence the policy effects of the tax. How the ITC of the carbon tax will affect the socioeconomic conditions and emission reduction is analysed through the result changes of the TL model relative to the CD model.

Data

As China Statistical Yearbooks have not published the coal price data, I have used the data from China Coal Industry (CCI 2016, 2017, 2018, 2019), shown in Table 4.1. Table 4.1 shows the variation of the coal and coke price in 2015–2018. Noticeably, there was a sharp increase in the coal price from 2015 to 2016, but the price remained stable in 2016–2018. In contrast, the coke price grew steadily in this period over 2015–2018.

Table 4.1 The Coal Price and Coke Price in 2015–2018 (Unit: CNY/tonne)

Year	2015	2016	2017	2018
Coal	370	639	611.7	620.7
Coke	569	787	1356	1528

As the Chinese authority has not published the official data of the petroleum price, I have calculated the weighted arithmetic average price of the petroleum in 2015–2018 using the published data in the annual reports of PetroChina Company Limited (PCCL 2017, 2019) and China Petroleum and Chemical Corporation (CPCC 2017, 2019).

Table 4.2 The Petroleum Prices in 2015–2018 (Unit: CNY/tonne)

Year	2015	2016	2017	2018
Crude Oil	2124	1865	2392	3207
Kerosene	3366	2832	3539	4553
Gasoline	6388	6091	6698	7492
Diesel Oil	4733	4316	4821	5734
Fuel Oil	2439	1892	2380	3335

Table 4.2 shows the variation of the different kinds of the petroleum prices in China in 2015–2018. The gasoline had the highest price, whilst the crude oil had the lowest price. Generally, the petroleum prices decreased from 2015 to 2016 but increased steadily in 2016–2018.

As the retail price of the natural gas in China is unavailable in the published statistical yearbooks, I have used the price data in the annual report of China Gas Holdings Limited (CGHL 2017, 2018, 2019), shown in Table 4.3. Noticeably, the 2015–2018 price of the natural gas, in this chapter, corresponds to the 2015/16, 2016/17, 2017/18, and 2018/19 fiscal year price of the natural gas in CGHL respectively. All the sectors, except for the transport, storage and post sector and service sector, are assumed to face the natural gas price for the industrial use, whilst these two sectors face the natural gas price for the commercial use.

Table 4.3 The Natural Gas Price in 2015–2018 (Unit: CNY/m^3)

Year	2015	2016	2017	2018
Household Use	2.29	2.36	2.40	2.52
Industrial Use	2.59	2.38	2.50	2.65
Commercial Use	2.68	2.55	2.60	2.79

Table 4.3 shows the variation of the natural gas price in China over the period 2015–2018. The natural gas price for the household use was the lowest, whilst the price for the commercial use was the highest. The price for the household use increased steadily; in contrast, the price for the industrial and commercial use decreased in 2015–2016 but increased in 2016–2018.

In this chapter, all the sectors are assumed to face the 2015–2017 electricity price for general industry and commerce published by the National Energy Administration (NEA 2016, 2017, 2018). The electricity price is assumed to be the same regardless of the generation sources. The Chinese government (CG 2018) announced that it would reduce the electricity price for general industry and commerce by 10% in 2018, and the target was met according to the 2019 government report (CG 2019). The 2019 report also announced a further 10% reduction in addition to the 2018 reduction (CG 2019). I assume that the Chinese government has met the 2019 target, and thus the electricity price decreased by 10% in 2018 and 2019 respectively.

Table 4.4 The Electricity Price in 2015–2019 (Unit: CNY/1000 kw.h)

Year	2015	2016	2017	2018	2019
Electricity	825.14	817.44	765.24	688.72	619.84

Table 4.4 shows the change of the electricity price in China in 2015–2019. The electricity price decreased steadily in this period, which is quite different from the other energy prices shown in Table 4.1–4.3.

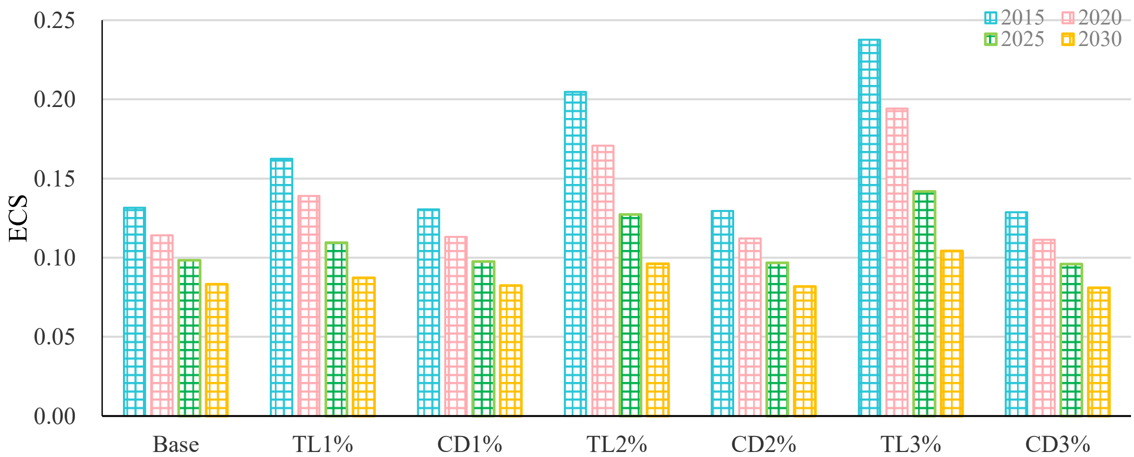
Table 4.5 The Energy Conversion Coefficients

Energy	Coal	Coke	Crude oil	Kerosene	Gasoline
Unit	kg (Scoal) / kg	kg (Scoal) / kg	kg (Scoal) / kg	kg (Scoal) / kg	kg (Scoal) / kg
Conv	0.71	0.97	1.43	1.47	1.47
Energy	Diesel Oil	Fuel Oil	Natural gas	Electricity	
Unit	kg (Scoal) / kg	kg (Scoal) / kg	kg (Scoal) /m^3	kg (Scoal) /kw.h	
Conv	1.46	1.43	1.22	0.12	

Note: The value for natural gas is the mean value.

Table 4.5 displays the conversion coefficients from the energies to the standard coal. With the same quantities, the liquid energies can be converted to more standard coals than the coal and coke. The units of the natural gas and electricity are different from the other energies, and thus these two energies cannot be directly compared to the other energies.

Model Results



Note: “TL” and “CD” refer to the Technical and CGE-DICE mode respectively; “Base” refers to the baseline scenario; “1%”, “2%”, “3%” refer to the 1%, 2%, 3% tax scenario respectively

Fig. 4.1 The Energy Cost Share (ECS) in the TL and CD Model

Fig. 4.1 displays the comparison of the energy cost share (ECS) between the two models over the studied period. In all the scenarios, the ECS will decrease gradually over time. In the tax scenarios, the ECS will remain at the same level as that in the baseline scenario without the ITC impact, but it will be larger than that in the baseline scenario with the ITC impact. As the tax rate increases, the ECS will increase in the TL model but remain relatively stable in the CD model. Fig. 4.1 implies that without the ITC impact, the rising energy price, induced by the carbon tax, will decrease the energy consumption, which explains why the ECS will remain stable in the CD model. As in the TL model the abatement costs are internalised in the energy consumption, the ECS will be much larger, compared to the CD model. This finding complies with Diaz and Puch (2019) who theoretically studied the relation between the energy demand and technical innovations, indicating that if the energy became scarcer under the carbon tax, the energy cost share would increase owing to the rising energy price.

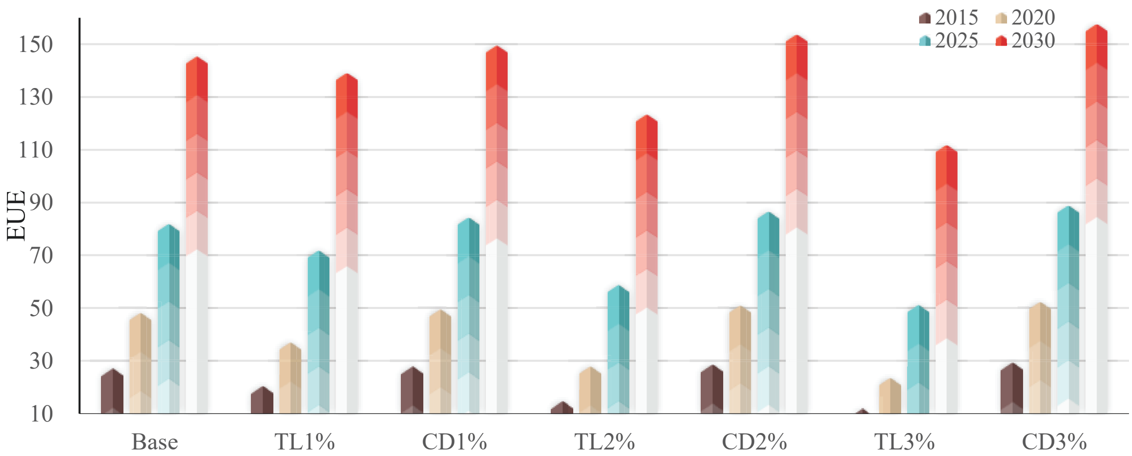


Fig. 4.2 The Energy-Use Efficiency (EUE) in the TL and CD Model

Fig. 4.2 shows the variation of the EUE over the studied period. In all the scenarios, the EUE will increase steadily over time, and this variable in 2030 will be more than fivefold the 2015 level. The carbon tax will increase the EUE, and this policy effect will be strengthened as the tax rate increases. The economic intuition underlying this result is that the carbon tax decreases the amount of energy to be consumed, and thus a rational entity has an incentive to use the limited amount of energy more efficiently. This finding is in line with Zhang and Zhong (2010) who designed the optimal Chinese carbon tax, indicating that the designed carbon tax increased the energy efficiency. According to Fig. 4.2, the ITC will slightly decrease the EUE, and this policy effect will be strengthened as the tax rate increases. This is because the ITC of the tax is more favourable to the development of the nonenergy sectors. Hence, as more resources are shifted away from the energy sectors, the EUE will decline.

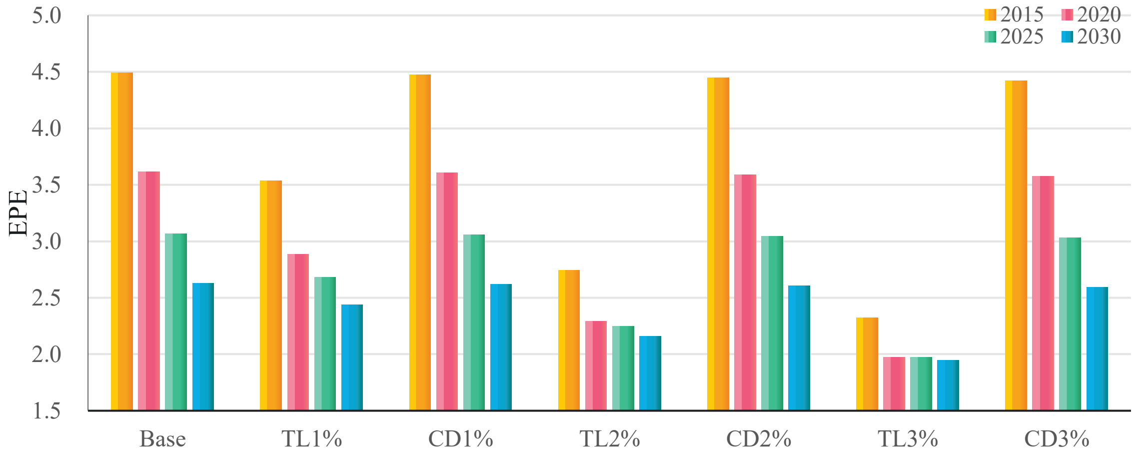


Fig. 4.3 The Energy-Production Efficiency (EPE) in the TL and CD Model

Fig. 4.3 shows how the EPE will change in the TL and CD model over time. In all the scenarios, the EPE will decrease steadily over the research period. Without the ITC impact, the carbon tax imposed on the nonrenewable energy sectors will only slightly decrease the EPE. This is because the tax increases the production costs of these sectors, and thus more resources will be shifted away, thereby reducing the R&D in energy production, according to Gerlagh (2008) who developed an endogenous growth model to measure the accumulated innovations globally in 1970–2000. The ITC will significantly decrease the EPE in the tax scenarios, implying that the ITC favours the technical innovation in the nonenergy sectors. As more resources are shifted away from the nonrenewable energy sectors, their output efficiency is likely to decrease considering the scale effect.

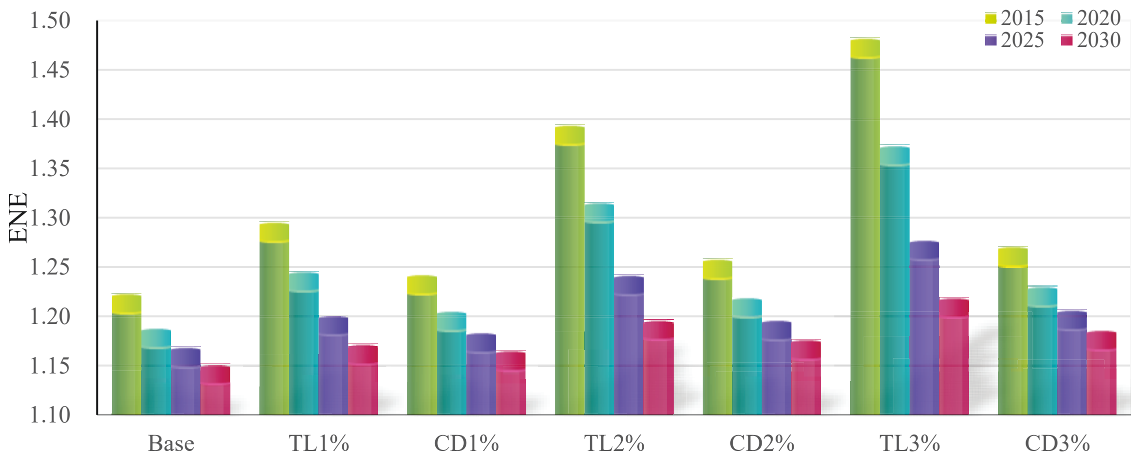


Fig. 4.4 The Nonenergy-Production Efficiency (ENE) in the TL and CD Model

Fig. 4.4 shows the changes of the ENE with and without the ITC impact over time. In all the scenarios, the ENE will decrease gradually over the studied period. The carbon tax will raise the ENE, and the increase of the tax rate will strengthen this policy effect. This is because the carbon tax will reduce the competitivity of the nonrenewable energy sectors, which results in the transfer of the social capital towards the nonenergy sectors (Chen, Zhou et al. 2017). Hence, the production efficiency of the nonenergy sectors will increase because of the scale effect. This finding complies with Wesseh and Lin (2020) who developed a dynamic equilibrium model to evaluate how the environmental policy affected the productivity, concluding that the carbon tax increased the multifactor productivity. In the tax scenarios, the ITC will further increase the ENE in addition to the policy effect of the tax, implying that the ITC induces disproportionately more supports for the nonenergy sectors. Similar empirical evidence can be found in Fried (2018) who developed a dynamic general equilibrium model with the endogenous technical innovation to show that the innovation amplified the price incentives of the carbon tax.

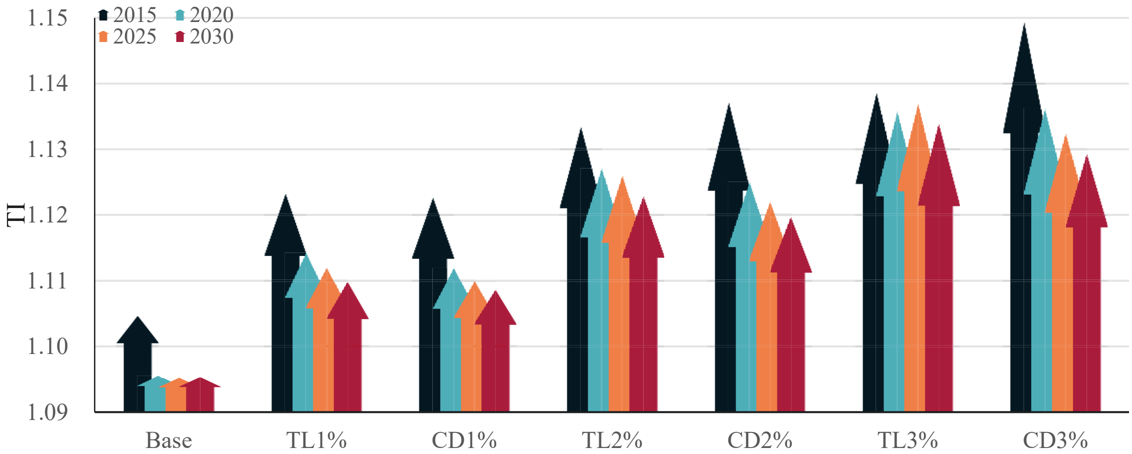


Fig. 4.5 The Technical Index (TI) in the TL and CD Model

Fig. 4.5 shows the TI changes in the baseline and tax scenarios simulated in the TL and CD model. In the baseline scenario, the TI decreased in 2015–2020 but will remain stable in 2020–2030. The carbon tax will increase the TI, but the TI will decline gradually over time in the tax scenarios. An increase in the tax rate will strengthen this policy effect on the TI. This finding abides by Jin (2012) who used an intertemporal CGE model to examine the impacts of the Chinese R&D, indicating that the carbon taxation could induce the technical innovation in China. The ITC will slightly increase the TI over time at the 1% tax, but it will only increase the TI since 2020 at the 2% and 3% tax. This result implies that the carbon tax rate will change the direction of the ITC impact on the TI. This finding complies with Goulder and Schneider (1999) used the general equilibrium models to investigate the importance of the ITC, concluding that climate policies had very different impacts on the R&D and thus did not necessarily enhance the technological progress at the country level.

Fig. A4.1 and A4.2 in Appendix A show how the household and total emissions will change in the TL model relative to that in the CD model. In the tax scenarios, the ITC will slightly reduce both the household and total emissions. However, when the tax rate increases, this policy effect will fluctuate over the studied period. This finding agrees with Goulder and Mathai (2000) who used the cost-effectiveness criterion to explore the significance of the ITC in climate policies, indicating that the ITC justified the greater overall abatement than would be warranted in its absence. The negative impacts of the ITC on the emissions correspond to the fact that under the ITC, the R&D-based and learning-by-doing based knowledge would be accumulated (Goulder and Mathai 2000) or more efficient and low-carbon technologies would be adopted (Laitner, Bernow et al. 1998).

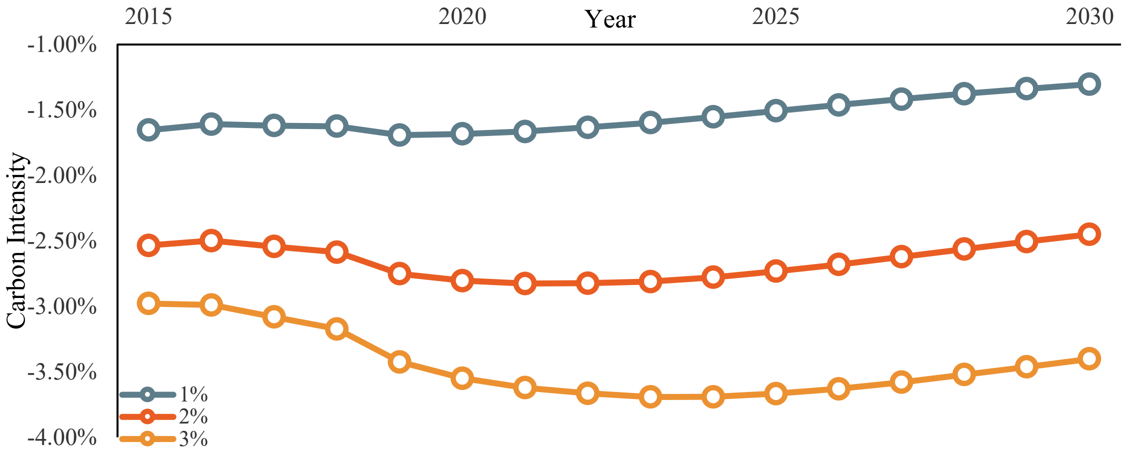


Fig. 4.6 The Carbon Intensity Change in the TL Model Relative to the CD Model

Fig. 4.6 shows the carbon intensity changes influenced by the ITC over time. According to Fig. 4.6, the ITC will decrease the intensity by 1%–4% depending on the tax rate and time. When the tax rate increases, this ITC impact will be strengthened, but it will fluctuate over the research period. Compared to the ITC impact on the emissions, the ITC will have a much more distinct impact on the intensity. The reason why the ITC will decrease the intensity is that energy consumption becomes more costly under the tax, and thus an entity has an incentive to exploit energy more efficiently. This finding agrees with Nordhaus (2002) who developed the DICE model to analyse the US Climate Change Technology Initiative, empirically showing that the ITC reduced the carbon intensity.

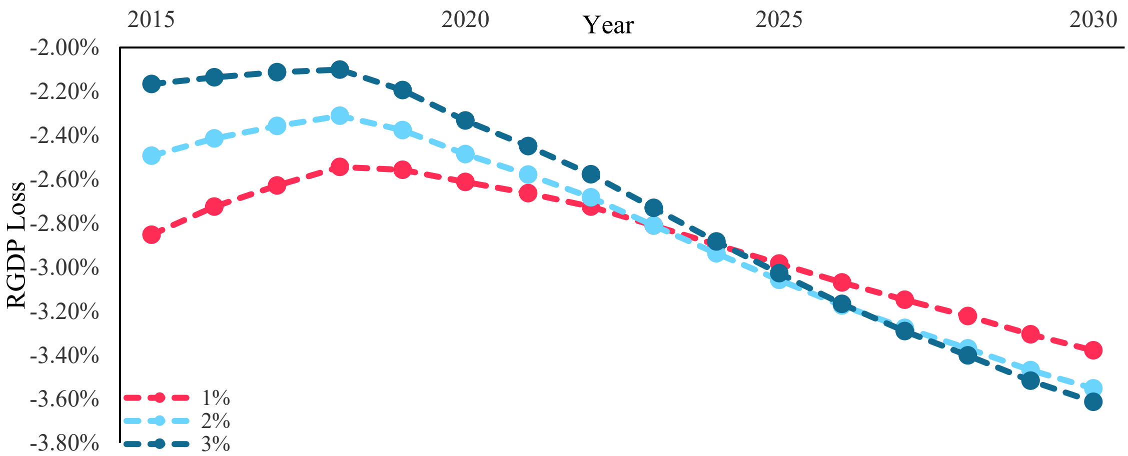


Fig. 4.7 The RGDP Loss Change in the TL Model Relative to the CD Model

Fig. 4.7 shows how the ITC will affect the RGDP loss over the studied period. According to Fig. 4.7, the ITC will reduce the RGDP loss by 2%–3.8% under the imposition of the carbon tax. In a time horizon, this impact decreased in 2015–2019 but will increase in 2020–2030. The reason why the ITC will increase the RGDP is that technical progress increases productivity and thus boosts economic growth, according to the Solow–Swan Growth model (Solow 1956). This finding complies with Popp (2004) who modified the DICE model to quantify the ITC in the energy sector, empirically showing that the welfare would improve by 9.4% when the ITC impact was considered.

Fig. A4.3 in Appendix A shows the change of the household welfare loss under the ITC impact. Unlike the RGDP loss, the household welfare loss, induced by the carbon tax, will be raised by the ITC over time. This ITC impact will be weakened as the tax rate increases. According to Fig. A4.3, the ITC impact on the household welfare is much smaller than that on the RGDP. This finding corresponds to the economic intuition that economic growth may not necessarily increase welfare. This is because economic growth may expand the wealth gap which decreases the overall welfare.

Fig. A4.4 in Appendix A shows the variation of the tax revenues under the ITC impact over time. According to Fig. A4.4, the ITC will negatively affect the tax revenues even though this impact is not significant. This finding is in line with Sands (2018) who used the Future Agricultural Resources Model to empirically show that the carbon tax revenues declined with the availability of a negative-emissions technology. Similarly, Muratori, Calvin et al. (2016) used the Global Change Assessment Model (GCAM) to explore the economic impacts of deploying bioenergy with carbon capture and storage, indicating that the tax revenues would be substantially lower with the availability of the carbon capture and storage technology.

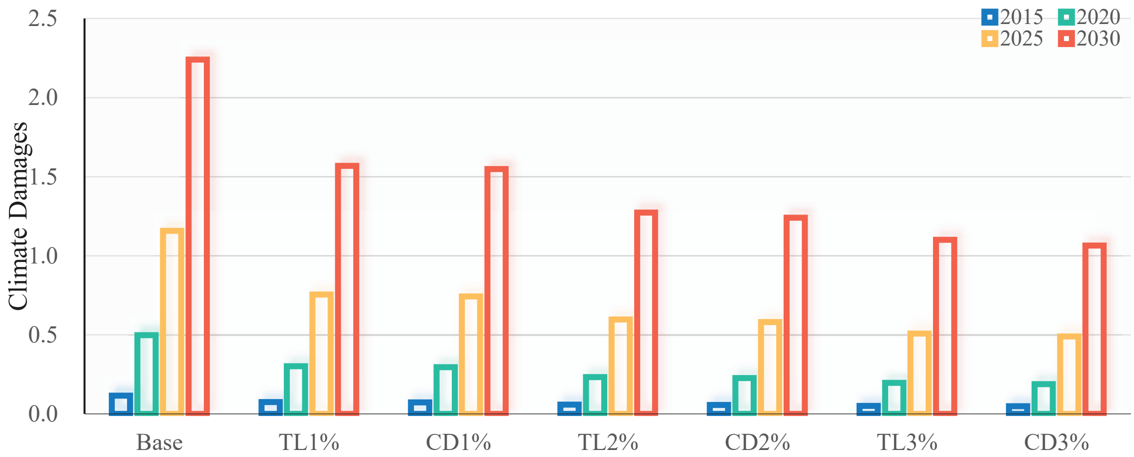


Fig. 4.8 The Climate Damages in the TL and CD Model (Unit: 10^{12} CNY)

Fig. 4.8 shows the climate damages in the TL and CD model over time. In all the scenarios, the climate damages will increase over the studied period. The carbon tax will reduce the damages, and this policy effect will be strengthened when the tax rate increases. This is because the tax, which curbs the combustion of the nonrenewable energy, will decelerate the global warming and thus reduce the climate damages. This finding agrees with the previous research showing that the climate control interventions to cap the global temperature rise would significantly reduce the cumulative damages from the climate change, according to Rasiah, Al-Amin et al. (2017) who analysed the implications of Malaysia's INDC. Fig. 4.8 also implies that the ITC will weaken the negative effect of the carbon tax on the climate damages. As the ITC will increase the economic output (shown in Fig. 4.7), the increasing human activities, like the deforestation, could induce more climate damages even though the ITC impact on the carbon intensity is negative.

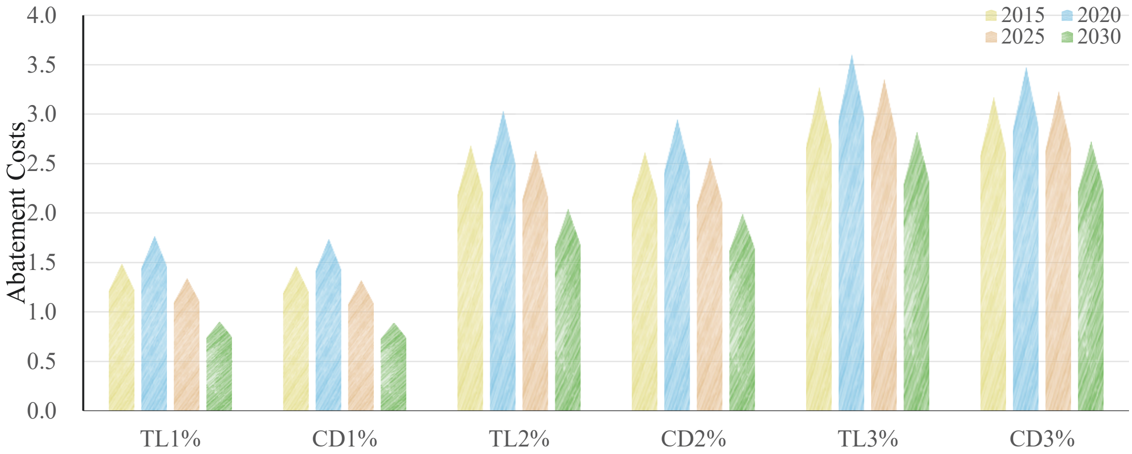


Fig. 4.9 The Abatement Costs in the TL and CD Model (Unit: 10^{12} CNY)

Fig. 4.9 shows the abatement costs, induced by the carbon tax, in the TL and CD model. In all the tax scenarios, the abatement costs increased in 2015–2020 but will decrease in 2020–2030. An increase in the tax rate will induce more abatement costs, implying that the abatement costs will rise if the mitigation target becomes stricter. The positive relation between the abatement costs and tax rate could be also found in Brenchley (2013) and Yang, Teng et al. (2018). Compared to the CD model, the TL model shows that the ITC will slightly increase the abatement costs. The reason why the ITC will increase the abatement costs is that the ITC will decrease the EUE and EPE, shown in Fig. 4.2 and 4.3 respectively. Hence, the emission abatement could become more costly if more R&D is shifted to the nonenergy sectors. This finding complies with Goulder and Mathai (2000) who explored the significance of the ITC in climate policies and found that the ITC increased the overall abatement costs.

Table 4.6 The Comparison of the Total Household Welfare (Unit: 10^{18} CNY)

Baseline	1%		2%		3%	
	TL	CD	TL	CD	TL	CD
15.5338	13.3048	13.3050	11.7422	11.7424	10.5461	10.5464

Table 4.6 shows the summation of the household welfare over the studied period in the TL and CD model. According to Table 4.6, the tax will drastically decrease the household welfare, whilst the ITC will only slightly decrease the welfare. The unappealing technical impact on the household welfare implies that when considering the ITC, the benefits of the economic boom will be counteracted by the increasing climate damages and abatement costs. From the household perspective, the most attractive scenario is the baseline scenario where no carbon tax is imposed. The deadweight loss, induced by the carbon tax, dominates the policy effect of the tax on the household welfare.

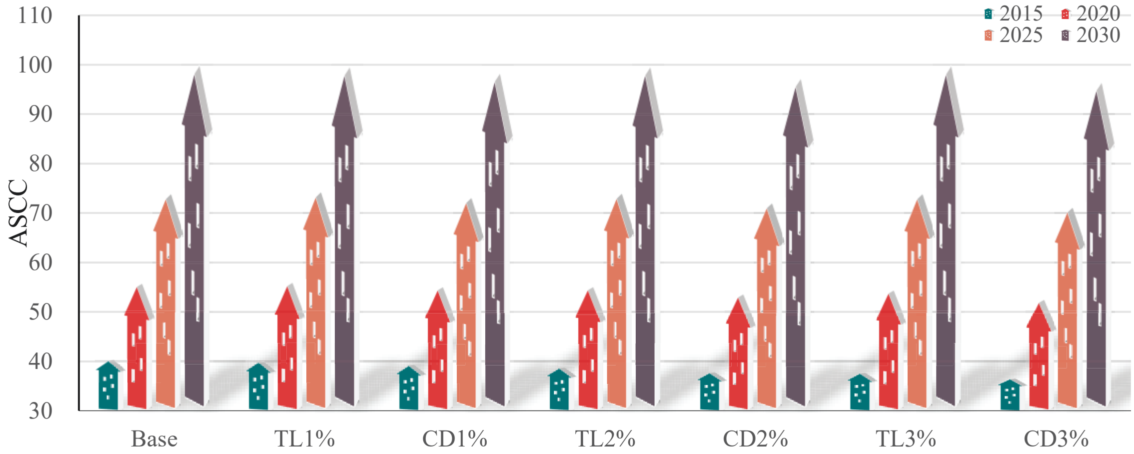


Fig. 4.10 The ASCC in the TL and CD Model (Unit: 2015 $\$/t\ CO_2$)

Fig. 4.10 shows how the average social cost of carbon (ASCC) will change under the ITC impact over the research period. In all the scenarios, the ASCC will increase over time, but it is minimally affected by the carbon tax. The ITC will slightly increase the ASCC in the tax scenarios, and the magnitude of this impact will be positively related to the tax rate. The rationale underlying Fig. 4.10 is that the ITC will increase the climate damages and thus the ASCC. This finding complies with Jensen and Traeger (2014) who evaluated the optimal mitigation policy using a stochastic integrated assessment model of the climate change, empirically showing that the technological growth would increase the ASCC at the positive economic growth rate.

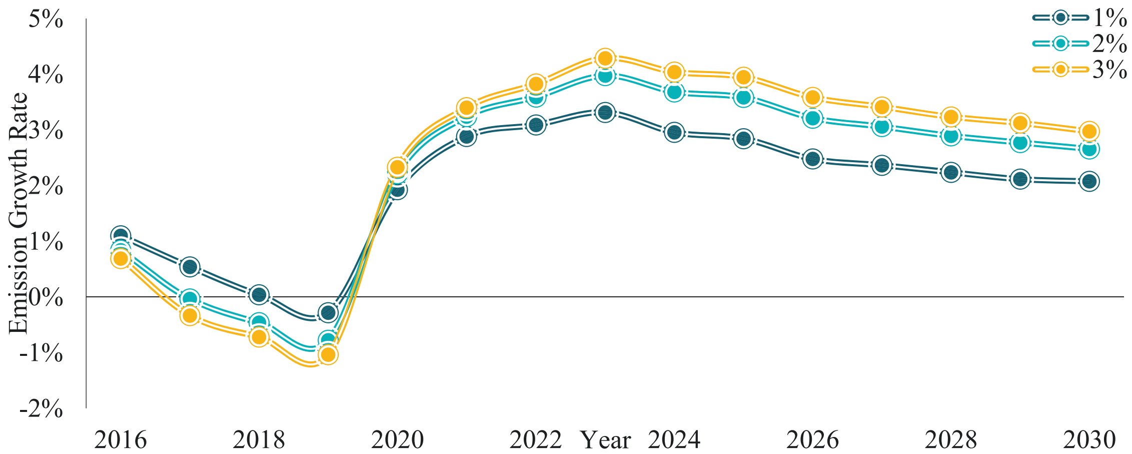


Fig. 4.11 The Annual Emission Growth Rate in the Tax Scenarios with the ITC Impact

Fig. 4.11 shows the ITC impact on the emission growth rate over the studied period. Considering the ITC impact in addition to the ancillary and primary benefit, the carbon tax still cannot help China meet the INDC target of peaking the emissions in 2030. As Fig. 4.6 shows the ITC negatively affects the carbon intensity, China will still meet the INDC target of the carbon intensity reduction in 2030 under the ITC impact of the carbon tax.

Discussion

This chapter empirically shows that without the ITC impact, the carbon tax will have almost no impact on the energy cost share. This finding is contrary to Wang, Liu et al. (2018) who empirically found the carbon pricing would increase the energy cost for the energy sectors. The result difference is due to the sectoral coverage of the carbon tax: the tax in Wang, Liu et al. (2018) covered the energy sectors only, whilst the tax in this chapter has covered the entire country.

The ITC will decrease the EUE in the tax scenarios. This finding disagrees with the previous research showing that the ITC improved the energy efficiency (Kemfert and Truong 2007). The result difference between Kemfert and Truong (2007) and this chapter lies in the socioeconomic conditions where the ITC impacts are analysed: Kemfert and Truong (2007) directly studied the ITC impacts caused by the increase of the R&D investment, whilst the ITC impacts are analysed under the carbon tax in this chapter. The socioeconomic conditions will affect the ITC impact on the energy-use efficiency. This is because a beneficial role of the technological progress on the energy efficiency improvement required the full play of the market power in the resource allocation, according to Li and Lin (2018) who used the dynamic panel data models to investigate the effects of the technological progress on the energy productivity in China. As the carbon tax is a kind of governmental interventions on the market mechanism, its distortion on the resource allocation is likely to induce the unexpected consequences to the ITC impact on the EUE.

The ITC will drastically decrease the EPE in the tax scenarios. This is because the ITC of the carbon tax favours the nonenergy sectors, and more resources are shifted to the production of the nonenergy goods. This finding complies with Macaluso, Tuladhar et al. (2018) who provided a cross-model analysis to investigate the policy effects of the carbon tax on the US industries, empirically showing that the carbon tax would induce the substitutions toward less carbon-intensive energy sources and production technologies. Hence, with resources shifted away, the energy sectors will have the lower EPE under the ITC impacts.

The ITC will increase the ENE because the ITC favours the nonenergy sectors. This finding complies with Ekins, Pollitt et al. (2012) who explored the implications of the EU environmental tax reform and empirically found that the environmental tax reform could increase the material productivity by 3.4%. Similarly, Chavas, Aliber et al. (1997) investigated the technical change with a focus on the R&D investments, indicating that the R&D had a large and positive effect on the agricultural productivity.

In the tax scenarios, the ITC will promote the technical progress at the lower tax rate. However, at the higher tax rate, the ITC inhibited the technical progress recently but will promote the progress in the future. The promotion impact of the ITC corresponds to the previous argument that a climate policy could induce additional R&D investment and knowledge application in carbon-saving innovations, according to Jin (2012) who used an intertemporal CGE model to examine the effectiveness of China's technical innovation on the emission abatement. In contrast, the inhibition impact of the ITC implies that owing to the socioeconomic constraints, the carbon pricing was ineffective to orientate the technical progress, according to Finon (2019) who explored the political economy constraints inhibiting the implementation of climate policies in developing countries.

The ITC will decrease the GDP loss induced by the carbon tax; in other words, the ITC will stimulate the economic growth. This is because technology is a production factor, which increases the productivity. Similar empirical evidence could be found in the previous research showing that the ITC would decrease the costs of the environmental tax, according to Liu and Yamagami (2018) who analysed the ITC impacts on the costs of the carbon tax in a static optimal tax model. Similarly, Kemfert (2005) used the multiregional and multi-sectoral integrated assessment model to investigate the economic impacts of climate policies, concluding that the ITC would support the carbon-free technologies and thus lead to an economic boom.

In contrast, the ITC will decrease the household welfare. This finding could be explained by the uncertainties existing in the household decision-making, according to Knobloch, Pollitt et al. (2019) who used the non-equilibrium bottom-up model to simulate the deep decarbonisation of residential heating. As the household may have very limited resources to cope with the rising price of the nonrenewable energies induced by the carbon tax, its welfare may decrease. Although the number of factors influencing the household choices regarding energy efficiency technologies is extensive, the economic factors are used as the key determinants for the technology choices (Mundaca, Neij et al. 2010).

The carbon tax will decrease the climate damages, and a similar result could be found in van der Meijden, Ryszka et al. (2018) who numerically investigated the climate damages and welfare effects of the climate policies in the climate-aware regions. As the anthropogenic emissions are considered as the main cause of the global warming (Rasiah, Al-Amin et al. 2017), the carbon tax, which mitigates the emissions, will relieve the global warming. However, the ITC will weaken this negative effect of the tax; in other words, the ITC will increase the climate damages. This finding could be explained by the positive impact of the ITC on the economic growth. As the economic impact of the ITC outweighs its negative impact on the emissions, hence, the ITC will increase the climate damages.

In this chapter, the ITC will increase the abatement costs over the studied period. This finding is contrary to Ahmed, Devadason et al. (2017) who adopted a calibrated model of climate analysis to assess the net gains of technical change, empirically showing that the technical change was effective to reduce the severe climate damages on the Pakistan agriculture. The result difference could be explained by the analysed scope of the ITC impact: in this chapter, the ITC affects the emission costs at the country level, whilst Ahmed, Devadason et al. (2017) mainly focused on the ITC in the agricultural sector.

According to Borlu and Glenna (2020) who used the survey data to test the climate change perception among the US specialty-crop producers, the agriculture was more susceptible to climate disruptions than many other industrial sectors. Hence, the unit benefit of the ITC to reduce the climate damages is much smaller at the country level than that at the agriculture sector. In addition, Loschel (2002) used the energy-economy-environment models to endogenously treat the ITC, empirically showing that the ITC decreased the abatement costs of the climate policy. This is because the model in Loschel (2002) emphasised the main elements of the technological innovation but neglected the economic impacts of the ITC. In the China example, the technical progress had a significant and positive effect on the economic growth (Wang 2012), which explained the expansion of the energy consumption (Li, Zhou et al. 2019) and thus the soaring anthropogenic emissions recently in China. Therefore, the ITC will increase the abatement costs in China.

Although the carbon tax will have almost no effect on the average social of carbon (ASCC), the ITC will slightly increase the ASCC. This finding is contrary to the previous argument that the ITC was conducive to enhancing the level of the emission abatement as well as reducing the social cost of the abatement, according to Wang, Mao et al. (2018) who employed a dynamic two-stage stochastic programming model to design the optimal low-carbon energy technologies. The result difference between Wang, Mao et al. (2018) and this chapter lies in the targeted scope of the ITC: Wang, Mao et al. (2018) only focused on the effect of the low-carbon energy policy on the ASCC, but they did not analyse the ITC of the climate policies; in contrast, this chapter has focused on the ITC impacts on the policy effects of the carbon tax.

In summary, the empirical results in this chapter generally fit in well with the previous research except that the result differences are mainly caused by the model assumptions and scope of the targeted sectors in the tax scenarios. However, as I have only modelled the induced technological change (ITC) of the carbon tax, this chapter cannot reveal the pure socioeconomic impacts of the technical progress. In the reality, the governmental policies targeted to promote the technical progress may be far more appealing than the carbon tax simulated in this chapter.

Another limitation of this chapter lies in the quantification method of the ITC. I have modelled the ITC based on Wang, Saunders et al. (2019) who argued that the ITC mainly included the potential changes of the energy-saving technologies but excluded the induced development of the decarbonisation or clean energies. The narrowed scope of the ITC is likely to underestimate the technical impacts. Future work may improve the quantification method of the ITC to include all types of the potential technologies that may be changed under the carbon tax.

The Tinbergen Rule states that there must be at least one policy tool for each policy target (Knudson 2009). The carbon tax, simulated in this paper, has already considered the ancillary and primary benefits, which may correlate with the ITC impacts. Future research may introduce the ITC impacts only in the CGE policy evaluation framework to study the net technical impacts. Alternatively, to achieve the largest technical benefits, an additional policy, like subsidies for the R&D in low-carbon technology, needs to be implemented.

Policy Implications

Considering the technical impacts of the carbon tax will increase the nonenergy-production efficiency, but it will decrease the energy-use and energy-production efficiency. Considering the technical impacts will strengthen the policy effects of the tax on the emission reduction, but it will weaken the negative effects of the tax on the household welfare and real GDP.

Conclusion

This chapter empirically shows that the carbon tax will significantly increase the energy cost share (ECS), and the ITC of the tax will further increase the ECS. By comparison, the carbon tax will increase the energy-use efficiency (EUE) and energy-production efficiency (EPE), but the ITC will decrease the EUE and EPE. In contrast, the carbon tax will increase the nonenergy-production efficiency (ENE), and the ITC will further increase the ENE in addition to the policy effect of the tax. The carbon tax will slightly increase the technical index; by comparison, the ITC will slightly increase the technical index over time at the 1% tax, but it will only increase the technical index since 2020 at the 2% and 3% tax.

The ITC will have minimal negative impacts on the carbon emissions. It will decrease the carbon intensity by 1%–4% depending on the tax rate and time. The ITC will have a negative impact on the RGDP loss, and the magnitude of this impact is 2%–3.8%. In contrast, the ITC will minimally increase the household welfare loss, induced by the carbon tax, implying that the ITC will decrease the household welfare. The carbon tax will reduce the climate damages, but this policy effect will be weakened by the ITC. By comparison, the ITC will increase the abatement costs induced by the carbon tax. The average social cost of carbon (ASCC) will remain relatively stable irrespective of the carbon tax, and it will be increased by the ITC.

Chapter 5: The Inequality Impacts of the Carbon Tax

Introduction

The positive impacts of the climate change on the generational inequality have received a great deal of attention in recent years (Burke, Hsiang et al. 2015, Moore and Diaz 2015). Despite the highest vulnerability to the climate change and possession of the least resources to adapt to extreme climate events and rising temperatures, the poorest and marginalized populations are least responsible for the past greenhouse gas emissions (Markkanen and Anger-Kraavi 2019). The disproportional climate burden on the poor is contrary to the spirit of the environmental justice which argues that "all people and communities are entitled to equal protection of environmental and public health laws and regulations" (Brulle and Pellow 2006).

The mismatch between the carbon emissions and burden of the climate change has been studied in the previous research (Althor, Watson et al. 2016). Higher energy price, induced by climate policies, is likely to undermine energy access, especially for the poor, and trap them in their current patterns of energy use (Jakob and Steckel 2014). Indeed, energy is related to the UN Millennium Development Goals (Modi, McDade et al. 2006) as well as the UNDP's Human Development Index (HDI) (Steinberger and Roberts 2010). The minimum energy requirement is of vital importance to individual and macroeconomic development (Pereira, Sena et al. 2011). Hence, the energy inaccessibility of the poor in the content of the climate change "can decisively hamper the political feasibility of respective reforms and provoke public resistance", according to Dorband, Jakob et al. (2019) who performed a global comparative analysis on the distributional effects of carbon pricing.

Considering the accelerating global warming recently, many researchers (Chen, Zhou et al. 2017, Yahoo and Othman 2017, Bi, Xiao et al. 2019) claimed for more climate policies to effectively relieve this phenomenon by curbing anthropogenic emissions. Unexpectedly, because low-income households spend a high share of their income on pollution-intensive goods (Klenert, Schwerhoff et al. 2018), most simulated climate policies in the literature appear regressive (Berry 2019). For example, Fremstad and Paul (2019) utilised the US input-output tables and household expenditure data, concluding that the tax exacerbated the inequality since the low-income households spent a greater share of their income on the carbon intensive goods. By assessing the impacts of including indigenous peoples in climate change mitigation, Brugnach, Craps et al. (2017) also argued that the existing climate policy would increase the inequality condition if the livelihoods of the poor were reduced. Similarly, Jiang and Shao (2014) used the input–output model and empirically found that the carbon tax could intensify the income inequality in Shanghai because the tax burden on the low-income subgroup was the highest. In summary, previous researchers, who concluded that a climate policy would increase inequality, tend to assume that the low-income subgroup faces the rising price of energy commodities without any protection from the government or society.

Despite the severe consequences of uneven energy allocation induced by climate policies, less attention has been given to the potentially adverse inequality impacts on the socioeconomic development (Markkanen and Anger-Kraavi 2019). Omitting inequality impacts is unlikely to simulate optimal climate policies because a complex and multi-layered relationship exists between income inequality and greenhouse gas emissions (Rao and Min 2018). The omission may also lead to biased evaluations of climate policies. For example, Bae (2018) adopted a joint estimation method to examine how global inequality affected emissions under climate policies, arguing that the inequality weakened the effectiveness of certain climate policies.

Previous researchers generally acknowledged that income inequality does affect economic growth; however, no consensus has been reached regarding the effect of inequality on growth (Caraballo, Dabus et al. 2017). By utilising a neoclassical growth model, Stiglitz (1969) argued for a positive relationship between inequality and economic growth owing to the saving rate, whilst Alesina and Perotti (1996) used a simple bivariate simultaneous equation model, concluding that the relationship was negative owing to the social instability. Nevertheless, researchers have generally believed that people will have negative feelings at the sight of another's good fortune (Bosmans and Ozturk 2018). Such feelings can be measured by relative utility, which indirectly relates to economic growth.

According to Pham (2008), relative utility postulates that individuals compare their income to a reference level. In other words, people's utility not only depends on their own income but also is relative to their reference groups (Michalos 1985, Hagerty and Veenhoven 2003). By examining the impacts of the income of a reference group on the individual well-being in Germany, Ferrer-i-Carbonell (2005) empirically found that the income of the reference group was as important as the own income for individual happiness. In the literature, there is a growing amount of the evidence on how income inequality is associated with mental health (Burns 2015) or human psychology (Huang and Nguyen 2016). Researchers used different terminologies to define the scope of relative utility, including happiness (Hagerty and Veenhoven 2003, Clark, Frijters et al. 2008), satisfaction level of workers (Clark and Oswald 1996), and personal life satisfaction (Georgellis, Tsitsianis et al. 2009). Although it is very hard to prove that human psychology measures utility, "the acceptance of subjective well-being measures as a direct proxy for utility has consequently opened up a wide range of opportunities to further inform theory and policy design" (Clark, Frijters et al. 2008).

Generally, previous research has agreed that subjective well-being is negatively correlated with relative utility (Clark and Oswald 1996, Hagerty and Veenhoven 2003, Clark, Frijters et al. 2008, Georgellis, Tsitsianis et al. 2009). An increase in income inequality is likely to increase the absolute value of the negative relative utility. Therefore, raising the overall income may not necessarily increase the average long-term happiness for the whole society, according to Hagerty and Veenhoven (2003) who tested the absolute utility theory against the relative utility theory. However, very little research has been performed to study the correlation between subjective well-being and relative utility. To my best knowledge, the first attempt to measure the consumer behaviour of relative risk aversion was the pioneering experiments conducted by Johansson-Stenman, Carlsson et al. (2002). Although the experiments were conducted in Sweden, the consumption behaviours of the participants facing different income distributions compared to their own incomes could be universal. As the utility is directly linked to the consumption goods, a Chinese household may behave similarly to the Swedish participants when the absolute or relative income changes.

This chapter contributes to the literature by innovatively quantifying the inequality impacts of the simulated carbon tax based on the consumer behaviour study of Johansson-Stenman, Carlsson et al. (2002). Considering the influences of the climate damages and abatement costs, the inequality condition is measured by the Palma ratio, and the inequality impacts are measured by the relative utility. How the tax revenue recycling policies affect the inequality impacts is also analysed in the designed 12 scenarios. In this chapter, the optimal condition of the model is the maximisation of the net welfare rather than the total welfare defined in the previous chapters. Finally, a sensitivity analysis is performed to show how the relative utility defined in this chapter is affected by the exogenously given parametric values.

Method

In this chapter, the empirical model is named as the inequality model. I start the analysis by dividing the representative household in the technical model (defined in the previous chapter) into three groups, namely the low-income, middle-income, and high-income subgroup. The low-income subgroup is the lowest 40% income households; the high-income subgroup is the highest 10% income households; the rest of the households belong to the middle-income subgroup. The household division is based on the 2013 Chinese Household Income Project (CHIP) conducted by China Institute for Income Distribution (CIID). The compiled data are summarised in Table 5.1.

Table 5.1 Income Ratios of Different Household Subgroups in 2013

Group	Overall	Labour	Capital	Transfer
Low-income	14.38%	10.03%	18.26%	23.38%
Middle-income	55.39%	57.43%	49.76%	57.67%
High-income	30.23%	32.55%	31.97%	18.95%

In Table 5.1, “Labour” denotes the income from the labour factor, which is from “wage income” in the 2013 CHIP data; “Capital” denotes the income from the capital factor, which is from the summation of “net business income” and “net property income” in the 2013 CHIP data; “Transfer” is the aggregated transfer income from the government, enterprise, and the rest of the world. In this chapter, the ratios of the income sources for each household subgroup are assumed to remain unchanged over the period 2015–2030. Because different income source will experience different growth rate, the overall income for each household subgroup will change, and thus the equality conditions will also change. The carbon tax will influence the income growth rate in different sources, which finally affects the income distribution among the household subgroups. The income from different sources among the household subgroups is shown in Eq. (5.1) to (5.3).

$$LIn_t = 10.03\% \times TYL_t + 18.26\% \times YHK_t + 23.38\% \times (YHG_t + YEH_t + YHW_t) \quad (5.1)$$

$$MIn_t = 57.43\% \times TYL_t + 49.76\% \times YHK_t + 57.67\% \times (YHG_t + YEH_t + YHW_t) \quad (5.2)$$

$$HIn_t = 32.55\% \times TYL_t + 31.97\% \times YHK_t + 18.95\% \times (YHG_t + YEH_t + YHW_t) \quad (5.3)$$

In Eq. (5.1) to (5.3), LIn_t, MIn_t, and HIn_t stand for the gross income of the low-income, middle-income, and high-income subgroup in Year t respectively. TYL_t refers to the household income from the labour factor, which is the summation of the sectoral household labour income in Year t. YHK_t denotes the household income from the capital factor in Year t. YHG_t, YEH_t, and YHW_t refer to the household income from the government, enterprise, and foreign transfer in Year t respectively.

In addition to the income distribution, the 2013 CHIP data also shows the distribution of the consumption in the surveyed households. The carbon tax that has different impacts on the various types of the consumption goods will affect the distribution of consumption among the household subgroups. Based on the 2013 CHIP data, Table 5.2 shows the calculated consumption ratios of different household subgroups.

Table 5.2 Consumption Ratios of Different Household Subgroups in 2013

Group	Overall	Food	Clothing	Transport	Service	Other Goods
Low-income	20.91%	24.90%	16.56%	15.72%	20.63%	15.22%
Middle-income	54.16%	55.08%	56.57%	53.47%	53.53%	50.11%
High-income	24.93%	20.02%	26.87%	30.81%	25.83%	34.68%

In Table 5.2, "Food" refers to "expenditure on food, tobacco, and alcohol" in the 2013 CHIP data. "Clothing" stands for "clothing expenditure". "Transport" represents "expenditure on communication and transportation". "Service" is the aggregation of "housing expenditure", "expenditure on facility and services", "expenditure on education and entertainment, and cultural activities", and "healthcare expenditure". "Other Goods" refers to "expenditure on miscellaneous goods and services". In this chapter, the ratios of the consumption goods among the household subgroups are assumed to remain unchanged over the studied period. The distribution of consumption goods among the household subgroups is shown in Eq. (5.4) to (5.6).

$$LTHD_t = 24.90\% \times HDFO_t + 16.56\% \times HDCL_t + 15.72\% \times HDTR_t + 20.63\% \times HDSE_t + 15.22\% \times HDOG_t \quad (5.4)$$

$$MTHD_t = 55.08\% \times HDFO_t + 56.57\% \times HDCL_t + 53.47\% \times HDTR_t + 53.53\% \times HDSE_t + 50.11\% \times HDOG_t \quad (5.5)$$

$$HTHD_t = 20.02\% \times HDFO_t + 26.87\% \times HDCL_t + 30.81\% \times HDTR_t + 25.83\% \times HDSE_t + 34.68\% \times HDOG_t \quad (5.6)$$

In Eq. (5.4) to (5.6), $LTHD_t$, $MTHD_t$, and $HTHD_t$ denote the total consumption of the low-income, middle-income, and high-income subgroup in Year t respectively. $HDFO_t$, $HDCL_t$, $HDTR_t$, $HDSE_t$ and $HDOG_t$ stand for the household consumption of food, clothing, transport, service, and the other goods in Year t respectively.

In addition to the uneven distribution of the income and consumption, the climate damages are also distributed unevenly among the household subgroups. The uneven distribution of the climate damages has become a significant part of the inequality issue induced by the climate change and its relating policies (Dennig, Budolfson et al. 2015). According to Dennig, Budolfson et al. (2015) who introduced a more fine-grained representation of inequalities in the RICE model, the relationship between damage distribution and income distribution can be denoted by the income elasticity of damage (ξ). Although Dennig, Budolfson et al. (2015) has not given the exact value of the ξ, the sign of the ξ could be used to denote the relationship: positive, zero, and negative ξ values imply that the climate damages are proportional, independent, and inversely proportional to the income respectively. Because the welfare function of the DICE model is related to the household consumption, the climate damages that the household suffers are divided into three groups. If ξ is positive, the division of the climate damages among the household subgroups is shown in Eq. (5.7).

$$\begin{cases} LDam_t = LTHD_t/THD_t \times Dam_t = LTHD_t \times damfrac_t \\ MDam_t = MTHD_t/THD_t \times Dam_t = MTHD_t \times damfrac_t \\ HDam_t = HTHD_t/THD_t \times Dam_t = HTHD_t \times damfrac_t \end{cases} \tag{5.7}$$

In Eq. (5.7), $LDam_t$, $MDam_t$, and $HDam_t$ are the climate damages suffered by the low-income, middle-income, and high-income subgroup in Year t respectively. THD_t is the total household consumption in Year t. Dam_t is the climate damages suffered by the household, and these damages are only part of the total climate damages. $damfrac_t$ denotes the damage ratio in the DICE model.

When ξ equals zero, the climate damages are assumed to be independent from the income. Hence, the distribution of the damages is only related to the percentage of the occupied population in each household subgroup, shown in Eq. (5.8). The population percentage data are from the division of the household subgroups mentioned above.

$$\begin{cases} LDam_t = 40\% \times Dam_t \\ MDam_t = 50\% \times Dam_t \\ HDam_t = 10\% \times Dam_t \end{cases} \tag{5.8}$$

$$\begin{cases} LDam_t = 69.7\% \times Dam_t \\ MDam_t = 27.8\% \times Dam_t \\ HDam_t = 2.5\% \times Dam_t \end{cases} \tag{5.9}$$

When ξ is negative, the low-income subgroup will suffer disproportionally more climate damages shown in Eq. (5.9). The damage ratios are from the "supporting information" in Dennig, Budolfson et al. (2015): the ratio for the low-income subgroup is the aggregation of the first and second quintiles;

the ratio for the middle class is the aggregation of the third and fourth quintiles and the first half of the fifth quintile; the ratio for the high-income subgroup is the second half of the fifth quintile. The embedded assumption of the division of the fifth quintile group is that the damages are evenly distributed. Noticeably, the aggregation of all the quintiles is equal to 99%, and thus all the ratios in this chapter have been amplified by 100% / 99% for the mathematic balance.

Based on the definition of the climate damages suffered by each household subgroup, the net consumption is equal to the total consumption deducted by the climate damages and abatement costs, shown in Eq. (5.10). YLL_t, YMM_t, and YHH_t denote the net consumption in the low-income, middle-income, and high-income subgroup in Year t respectively. $abate_t$ is the abatement ratio in Year t from the DICE model, and the ratio is assumed to be evenly distributed across the Chinese population.

$$\begin{cases} YLL_t = (LTHD_t - LDam_t) \times (1 - abate_t) \\ YMM_t = (MTHD_t - MDam_t) \times (1 - abate_t) \\ YHH_t = (HTHD_t - HDam_t) \times (1 - abate_t) \end{cases} \tag{5.10}$$

$$c_t = (YLL_t + YMM_t + YHH_t) \div POP_t \tag{5.11}$$

Therefore, the per capita net consumption for the whole country equals the summation of the net consumption of the household subgroups divided by the total population, shown in Eq. (5.11). c_t refers to the per capita net consumption in Year t; POP_t denotes the Chinese population in Year t.

Based on the per capita net consumption, the welfare function in the DICE model defines the annual and total welfare, shown in Eq. (5.12) and (5.13) respectively. $ANHW_t$ denotes the annual household welfare. r_t is the social discount rate in Year t, and its value is from the DICE model. η measures the elasticity of the marginal utility of consumption, also known as the inequality parameter in the DICE model. HW refers to the absolute household welfare over the studied period, which is defined as the summation of the annual welfare.

$$ANHW_t = (\frac{{c_t}^{1-\eta}}{1-\eta} - 1) \times POP_t \times r_t \tag{5.12}$$

$$HW = \sum_t ANHW_t \tag{5.13}$$

In the literature, Gini coefficient is widely used to denote income inequality. However, Gini coefficient is oversensitive to changes in the middle of income distribution and less sensitive to changes at the extremes, and thus it is not an ideal tool to analyse the current inequality patterns characterised by stable income share of middle classes and high fluctuations on the tails (Campagnolo and Davide 2019). In contrast, the Palma ratio focuses on the top and bottom classes of income distribution, which is more appropriate to the current inequality patterns (Cobham, Schlogl et al. 2016). The Palma ratio is defined as "the ratio of the top 10% of population's share of gross national income (GNI), divided by the poorest 40% of the population's share of GNI" (Campagnolo and Davide 2019). Considering the climate damages and abatement costs, in this chapter, the net income data are used to define the Palma ratio shown in Eq. (5.14). $Palma_t$ refers to the Palma ratio in Year t; $Linco_t$ and $Hinco_t$ are the net income for the low-income and high-income subgroup respectively in Year t. The net income for each household subgroup is defined as the gross income subtracted by the climate damages and abatement costs.

$$Palma_t = Hinco_t / Linco_t \tag{5.14}$$

Because the poorest populations are least responsible for the historical emissions but possess the least resources to adapt to the accelerating climate change, the abatement costs should be only paid by the high-income subgroup (Markkanen and Anger-Kraavi 2019). On the contrary, the rich have much higher per capita carbon emission than the poor (Padilla and Serrano 2006), and they have more resources to adapt to the rising global temperature. Eq. (5.15) to (5.17) show the income distribution when the high-income subgroup pays the abatement costs. The three equations denote the cases when the income elasticity of damage (ξ) is positive, zero or negative. YHT_t refers to the total household income in Year t, and it equals the summation of LIn_t, MIn_t and HIn_t.

$$\begin{cases} Linco_t = LIn_t \times (1 - damfrac_t) \\ Minco_t = MIn_t \times (1 - damfrac_t) \\ Hinco_t = HIn_t \times (1 - damfrac_t) - YHT_t \times (1 - damfrac_t) \times abate_t \end{cases} \tag{5.15}$$

$$\begin{cases} Linco_t = LIn_t - YHT_t \times damfrac_t \times 0.4 \\ Minco_t = MIn_t - YHT_t \times damfrac_t \times 0.5 \\ Hinco_t = HIn_t - YHT_t \times damfrac_t \times 0.1 - YHT_t \times (1 - damfrac_t) \times abate_t \end{cases} \tag{5.16}$$

$$\begin{cases} Linco_t = LIn_t - YHT_t \times damfrac_t \times 0.697 \\ Minco_t = MIn_t - YHT_t \times damfrac_t \times 0.278 \\ Hinco_t = HIn_t - YHT_t \times damfrac_t \times 0.025 - YHT_t \times (1 - damfrac_t) \times abate_t \end{cases} \tag{5.17}$$

If the abatement costs are proportional to the income, Eq. (5.18) to (5.20) show the net income for each household subgroup when ξ is positive, zero, and negative respectively.

$$\begin{cases} Linco_t = LIn_t \times (1 - damfrac_t) \times (1 - abate_t) \\ Minco_t = MIn_t \times (1 - damfrac_t) \times (1 - abate_t) \\ Hinco_t = HIn_t \times (1 - damfrac_t) \times (1 - abate_t) \end{cases} \tag{5.18}$$

$$\begin{cases} Linco_t = (LIn_t - YHT_t \times damfrac_t \times 0.4) \times (1 - abate_t) \\ Minco_t = (MIn_t - YHT_t \times damfrac_t \times 0.5) \times (1 - abate_t) \\ Hinco_t = (HIn_t - YHT_t \times damfrac_t \times 0.1) \times (1 - abate_t) \end{cases} \tag{5.19}$$

$$\begin{cases} Linco_t = (LIn_t - YHT_t \times damfrac_t \times 0.697) \times (1 - abate_t) \\ Minco_t = (MIn_t - YHT_t \times damfrac_t \times 0.278) \times (1 - abate_t) \\ Hinco_t = (HIn_t - YHT_t \times damfrac_t \times 0.025) \times (1 - abate_t) \end{cases} \tag{5.20}$$

By comparison, the abatement costs could be independent from the gross income, which means that the costs are only correlated with the population percentage that a household subgroup occupies. On this independent assumption, Eq. (5.21) to (5.23) show the net income for each household subgroup when ξ is positive, zero, and negative respectively.

$$\begin{cases} Linco_t = LIn_t \times (1 - damfrac_t) - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.4 \\ Minco_t = MIn_t \times (1 - damfrac_t) - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.5 \\ Hinco_t = HIn_t \times (1 - damfrac_t) - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.1 \end{cases} \quad (5.21)$$

$$\begin{cases} Linco_t = LIn_t - YHT_t \times damfrac_t \times 0.4 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.4 \\ Minco_t = MIn_t - YHT_t \times damfrac_t \times 0.5 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.5 \\ Hinco_t = HIn_t - YHT_t \times damfrac_t \times 0.1 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.1 \end{cases} \quad (5.22)$$

$$\begin{cases} Linco_t = LIn_t - YHT_t \times damfrac_t \times 0.697 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.4 \\ Minco_t = MIn_t - YHT_t \times damfrac_t \times 0.278 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.5 \\ Hinco_t = HIn_t - YHT_t \times damfrac_t \times 0.025 - YHT_t \times (1 - damfrac_t) \times abate_t \times 0.1 \end{cases} \quad (5.23)$$

According to Johansson-Stenman, Carlsson et al. (2002), the relative utility function for each household subgroup is defined in Eq. (5.24) where $ALco_t = Linco_t \div (0.4 \times POP_t)$, $AMco_t = Minco_t \div (0.5 \times POP_t)$ and $AHco_t = Hinco_t \div (0.1 \times POP_t)$. $ALco_t$, $AMco_t$, and $AHco_t$ stand for the average net income for the low-income, middle-income, and high-income subgroup in Year t respectively; $AIco_t$ refers to the average net income. $ARLUti_t$, $ARMUti_t$, and $ARHUti_t$ refer to the average relative utility for the low-income, middle-income, and high-income subgroup in Year t respectively.

$$\begin{cases} ARLUti_t = \frac{1}{1-\gamma_2}(ALco_t \times AIco_t{}^{-\gamma_1})^{1-\gamma_2} \\ ARMUti_t = \frac{1}{1-\gamma_2}(AMco_t \times AIco_t{}^{-\gamma_1})^{1-\gamma_2} \\ ARLUti_t = \frac{1}{1-\gamma_2}(AHco_t \times AIco_t{}^{-\gamma_1})^{1-\gamma_2} \end{cases} \quad (5.24)$$

In Eq. (5.24), the parameter γ_1 stands for the weight that an individual attaches to the relative income (Johansson-Stenman, Carlsson et al. 2002). The value of γ_1 lies between 0 and 1, with the extreme value 0, denoting that the relative utility does not depend on the relative income, and the extreme value 1, denoting that the relative utility only depends on the positional effect of the individual's income relative to the average national income (Johansson-Stenman, Carlsson et al. 2002). By default, in this chapter, γ_1 is assumed to equal 0.35, which was the median value of the positional experiment by Johansson-Stenman, Carlsson et al. (2002).

The parameter γ_2 measures the rate at which the relative utility falls as the income rises, according to Howarth and Kennedy (2016) who empirically showed the relation between income and well-being in a classical utilitarian ethical framework. By default, in this chapter, γ_2 is assumed to equal 1.72, which was the median value of the risk (inequality) aversion experiment by Johansson-Stenman, Carlsson et al. (2002). This value is quite close to 1.8 given by Howarth and Kennedy (2016). The value of γ_2 can range from negative infinitive to positive infinitive. However, to make the definition of the relative utility abide by the literature that rising income inequality will decrease the relative utility, the value of γ_2 is assumed to be larger than one. This assumption is rational as the majority of the participants in the experiment of Johansson-Stenman, Carlsson et al. (2002) had the relative risk aversion larger than one.

After the relative utility for each household subgroup is defined, the total relative utility is defined as the weighted summation of the relative utility in each household subgroup, shown in Eq. (5.25). $RUti$ denotes the overall relative utility for China over the studied period. Because the value of γ_2 is larger than one, the relative utility defined in Eq. (5.25) is always negative. The negative value of the relative utility implies that if the national income remains fixed, an increase in the income inequality will induce an increase in the absolute value of the negative relative utility.

$$RUti = \sum_t (ARLUti_t \times 0.4 + ARMUti_t \times 0.5 + ARHUti_t \times 0.1) \times POP_t \tag{5.25}$$

Based on the definition of the overall relative utility, the net welfare is defined as the overall welfare minus the absolute value of the relative utility, shown in Eq. (5.26). NHW refers to the net household welfare. Noticeably, the unit of the absolute welfare is 10^{18} CNY in the result section. The unit of $RUti$ is defined as $10^6 \times 100^{1-\gamma_1}$ CNY, depending on the value of γ_1. If $\gamma_1 = 0$, the unit of $RUti$ is 10^8 CNY, which means that the relative utility does not relate to the relative income; If $\gamma_1 = 1$, the unit of $RUti$ is 10^6 CNY, which means that the relative utility only relates to the relative income. From the unit difference between the total welfare and relative utility, the former is overwhelming larger than the latter. Therefore, the impact of the relative utility on the total welfare is negligible even though I have changed the optimum condition of the model from the maximisation of the total welfare to the net welfare.

$$NHW = HW - |RUti| \tag{5.26}$$

A sensitivity test has been performed to check how susceptible the relative utility is to the given parametric values of γ_1 and γ_2. Derived from the experiments in Johansson-Stenman, Carlsson et al. (2002), γ_1 and γ_2 were used to denote the participants' attitudes toward the relative income and risk. The experimental participants were the students from a Swedish university, and thus the participant selection may induce the parametric uncertainties. This is because participants from other social class or other countries may respond very different from the participated students in the experiments. Moreover, the participants' behaviours were monitored under the hypothetical society; however, socioeconomic factors, like an economic recession or recovery, could affect the behaviours. In the sensitivity analysis, the value of γ_1 is assumed to change freely from -50% to 50%, while the value of γ_2 is assumed to change freely from -40% to 50%. This is because if γ_2 changes by -50%, the value of γ_2 will be lower than 1, which violates its definition.

Scenarios

Depending on the taxpayers, the abatement costs can be paid by the high-income subgroup only, proportionally to the income and independently from the income. The abatement costs paid by the high-income subgroup only means that the middle-class and low-income subgroup do not have obligation to mitigate the climate change. The abatement costs paid proportionally implies that the middle-class and low-income subgroup have less obligation to abate the emissions compared to the high-income subgroup. The abatement costs allocated independently from the income means that the payment of the abatement costs is only related to the scale of the household subgroup.

Then this chapter analyses how recycling the tax revenues affects the inequality condition and relative utility. The tax revenues can be detained by the government, recycled to the enterprise, evenly to the household, and only to the low-income household. Recycling the revenues evenly to the household means the recycling is only related to the scale of a household subgroup. Recycling the revenues to the low-income subgroup corresponds to the fact that the low-income people are more susceptible to the losses induced by the climate change, but they are less responsible for the anthropogenic carbon emissions implied by the previous research (Jakob and Steckel 2014, Althor, Watson et al. 2016, Markkanen and Anger-Kraavi 2019). In this recycling policy, the livelihood loss of the low-income subgroup induced by the climate change is compensated disproportionally more from the recycling of tax revenues. The tax revenues could be also recycled to the enterprise because the most efficient way to use the revenues could be the capital formation (Caron, Cohen et al. 2018, Jorgenson, Goettle et al. 2018).

Table 5.3 The Designed Scenarios in This Chapter

Scenarios	To Whom the Tax Revenues Are Recycled	Who Pay the Abatement Costs
SCRO1	Government	High-Income Subgroup Only
SCRO2	Government	Proportionally to the Income
SCRO3	Government	Independently from the Income
SCRO4	Household Evenly	High-Income Subgroup Only
SCRO5	Household Evenly	Proportionally to the Income
SCRO6	Household Evenly	Independently from the Income
SCRO7	Low-Income Subgroup Only	High-Income Subgroup Only
SCRO8	Low-Income Subgroup Only	Proportionally to the Income
SCRO9	Low-Income Subgroup Only	Independently from the Income
SCRO10	Enterprise	High-Income Subgroup Only
SCRO11	Enterprise	Proportionally to the Income
SCRO12	Enterprise	Independently from the Income

Table 5.3 shows the designed 12 scenarios in this chapter, based on the recipients of the tax revenues and payers of the abatement costs. In each scenario, the climate damages are assumed to be positively related, independently from, and negatively related to the income.

Model Results

Table 5.4 The Palma Ratio in SCRO1

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.26	2.27	2.28	1.89	1.90	1.91	1.61	1.62	1.62
2020	2.51	2.55	2.58	2.28	2.31	2.34	2.00	2.03	2.06	1.79	1.82	1.85
2025	2.52	2.58	2.63	2.40	2.46	2.51	2.24	2.29	2.34	2.10	2.15	2.20
2030	2.55	2.63	2.71	2.49	2.57	2.65	2.40	2.48	2.55	2.32	2.40	2.47

Note: “Posi”, “Zero” and “Nega” refers to the positive, zero, and negative value of ξ respectively

Table 5.4 shows the Palma ratio in SCRO1 when the tax revenues are kept in the governmental budget, and the abatement costs are paid by the high-income subgroup only. When the income elasticity of damage (ξ) is zero or negative, the inequality condition will increase over time in all the tax scenarios. By comparison, when ξ is positive, the inequality condition will decrease first and then increase until 2030. The reason why the assumption of ξ changes the inequality condition is that the share of climate damages will directly affect the net income of a household subgroup and thus change the inequality condition. According to Table 5.4, as the tax rate increases, the Palma ratio will decrease. This finding is contrary to the previous argument that most climate policies appeared regressive (Berry 2019). The economic intuition underlying the progressivity of the carbon tax is that as the high-income subgroup consumes much more energies than the low-income subgroup, the carbon tax will decrease the net income of the high-income subgroup disproportionately more than the average level.

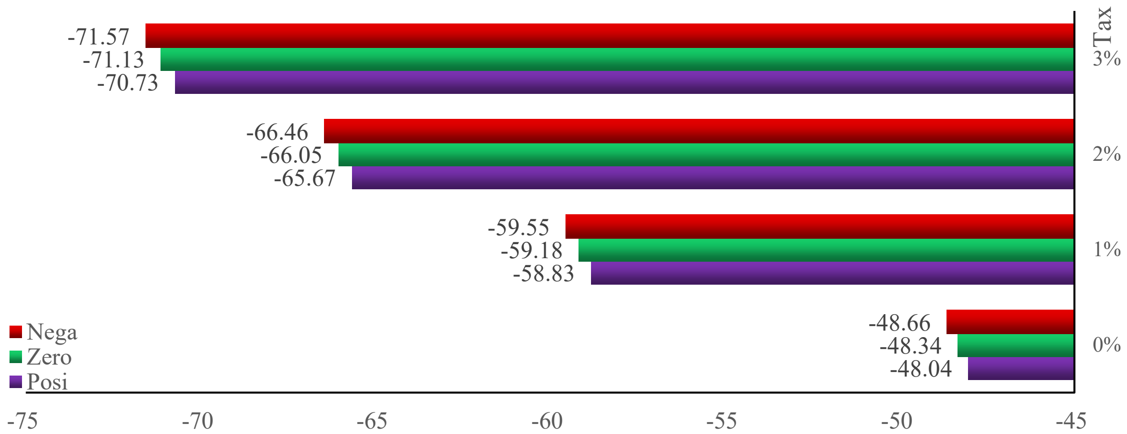


Fig. 5.1 The Relative Utility (RU) in SCRO1 (Unit: 10^9 CNY)

Fig. 5.1 shows how the carbon tax will affect the relative utility (RU) in SCRO1. With the fixed tax rate, the absolute value of the RU will be the lowest, when ξ is positive; it will be the highest, when ξ is negative. Although Table 5.4 shows the carbon tax will reduce the inequality condition, however, Fig. 5.1 implies that the taxation will induce more negative relative utility than the baseline scenario, and the absolute value of the RU is negatively related to tax rate. This is because the carbon tax will induce the deadweight loss and reduce the gross income for all the household subgroups. This finding implies that the absolute income is the main determinant of the RU even though the inequality condition does affect the RU.

Table 5.5 The Palma Ratio in SCRO2

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.54	2.55	2.56	2.54	2.55	2.56	2.54	2.55	2.56
2020	2.51	2.55	2.58	2.51	2.54	2.58	2.51	2.54	2.57	2.50	2.54	2.57
2025	2.52	2.58	2.63	2.51	2.57	2.62	2.51	2.57	2.62	2.51	2.57	2.62
2030	2.55	2.63	2.71	2.54	2.62	2.70	2.54	2.62	2.70	2.54	2.62	2.69

Table 5.5 shows the Palma ratio in SCRO2 assuming that the tax revenues are kept in the governmental budget, and the abatement costs are paid proportionally to the income. The baseline Palma ratio in Table 5.5 is the same as that in Table 5.4. This is because the abatement costs are zero in

the baseline scenario, and thus the allocation of the costs has no impacts on the Palma ratios. The Palma ratio in the tax scenarios of Table 5.5 is larger than that in Table 5.4. This is because the low-income subgroup will have the lower net income, and the high-income subgroup will have the higher net income, when the abatement costs are allocated proportionally to the income. Noticeably, in the tax scenarios, the Palma ratio will respond minimally to the variation of the tax rate. This is because each household subgroup will bear the same proportion of the abatement costs to the gross income.

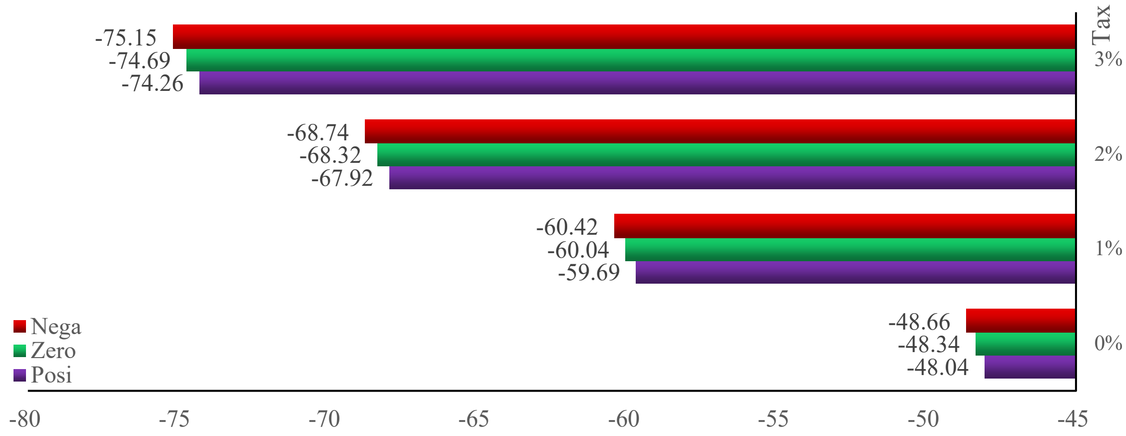


Fig. 5.2 The Relative Utility (RU) in SCRO2 (Unit: 10^9 CNY)

Fig. 5.2 shows the variation of the RU in the baseline and tax scenarios of SCRO2. The RU in the baseline scenario of Fig. 5.2 is equal to that in Fig. 5.1. However, the absolute value of the RU in Fig. 5.2 is larger than that in Fig. 5.1, because SCRO2 will induce the higher inequality condition compared to SCRO1. This finding complies with Clark, Frijters et al. (2008) who discussed the relation between happiness and utility, indicating that the increase of the income gap would reduce the happiness and thus increase the relative utility. At the same tax rate, the absolute value of the RU in Fig. 5.2 is only slightly larger than that in Fig. 5.1. This result implies that the absolute income is the main determinant of the RU. This finding conforms to Hagerty and Veenhoven (2003) who applied a dynamic model to revisit the wealth and happiness, concluding that contrary to the relative utility theory, the increasing national income would induce the increasing national happiness.

Table 5.6 The Palma Ratio in SCRO3

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.83	2.85	2.86	3.34	3.36	3.38	3.89	3.92	3.95
2020	2.51	2.55	2.58	2.73	2.78	2.81	3.08	3.13	3.18	3.40	3.46	3.53
2025	2.52	2.58	2.63	2.62	2.68	2.74	2.79	2.86	2.93	2.95	3.03	3.10
2030	2.55	2.63	2.71	2.59	2.67	2.75	2.67	2.76	2.85	2.76	2.85	2.94

Table 5.6 shows the Palma ratio in SCRO3 where the tax revenues are kept in the governmental budget, and the abatement costs are paid independently from the income. The Palma ratio in the tax scenarios of SCRO3 is much larger than that in Table 5.4 and Table 5.5. This is because in SCRO3, the low-income subgroup will disproportionally pay 40% of the abatement costs, whilst the high-income subgroup will only pay 10% of the costs. Noticeably, the inequality condition in the tax scenarios is

larger than that in the baseline scenario, implying that the tax is regressive if the abatement costs are independent from the income.

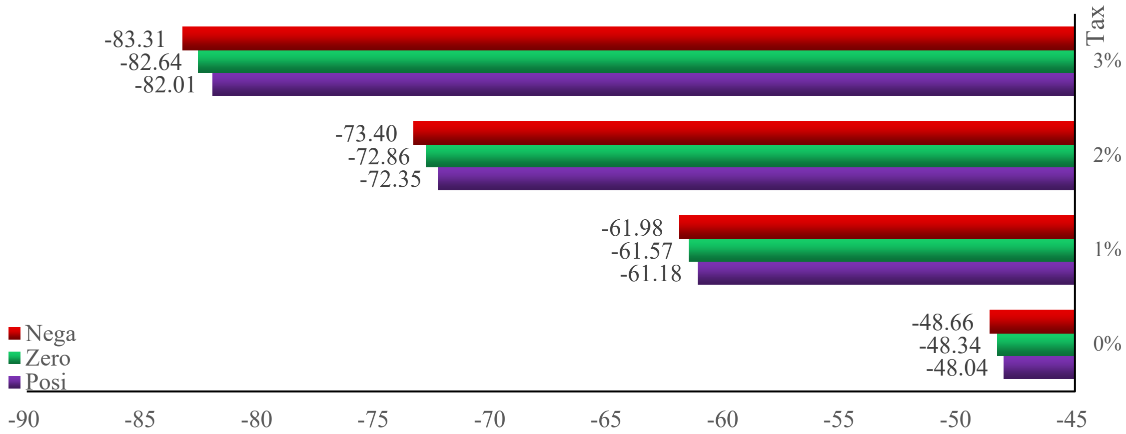


Fig. 5.3 The Relative Utility (RU) in SCRO3 (Unit: 10^9 CNY)

Corresponding to Table 5.6, the absolute value of the RU in Fig. 5.3 is much higher than that in Fig. 5.1 and 5.2. This result implies that given the absolute national income, the absolute value of the RU is positively related to the inequality condition. This finding fits in with Clark and Oswald (1996) who explored the data of 5000 British workers to test whether the utility depended on the income relative to a reference level, concluding that workers' satisfaction levels were inversely related to their comparison wage rates.

Table 5.7 The Palma Ratio in SCRO4

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.25	2.27	2.28	1.88	1.89	1.90	1.60	1.61	1.61
2020	2.51	2.55	2.58	2.27	2.31	2.34	1.99	2.02	2.05	1.78	1.81	1.84
2025	2.52	2.58	2.63	2.40	2.45	2.50	2.23	2.28	2.33	2.09	2.14	2.19
2030	2.55	2.63	2.71	2.49	2.57	2.64	2.40	2.47	2.55	2.31	2.39	2.46

Table 5.7 shows the Palma ratio in SCRO4 when the tax revenues are recycled evenly to the household, and the abatement Costs are paid by the high-income subgroup only. In the tax scenarios, the Palma ratio is lower in SCRO4 than that in SCRO1, implying that recycling the revenues from climate policies evenly to the household is beneficial to reducing the inequality. This finding agrees with Davies, Shi et al. (2014) who tested the possibilities of eliminating the global inequality using the tax revenues, empirically showing that redistributing the revenues of the carbon tax globally via equal per capita transfers would reduce the global Gini coefficient.

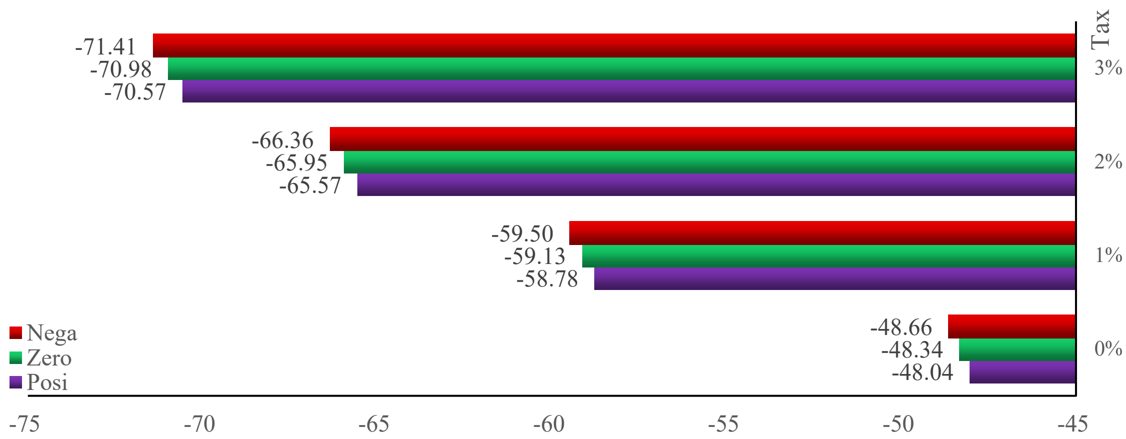


Fig. 5.4 The Relative Utility (RU) in SCRO4 (Unit: 10^9 CNY)

Fig. 5.4 shows the RU under the influence of recycling the tax revenues evenly to the household. The absolute value of the RU in Fig. 5.4 is smaller than that in Fig. 5.1. On the assumption of recycling the tax revenues evenly to the household, Table A5.1 and Fig. A5.1 in Appendix A show the Palma ratio and RU in SCRO5, when the abatement costs are proportional to the income; Table A5.2 and Fig. A5.2 in Appendix A show the Palma ratio and RU in SCRO6, when the abatement costs are independent from the income.

Table 5.8 The Palma Ratio in SCRO7

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.24	2.26	2.27	1.87	1.88	1.89	1.58	1.59	1.60
2020	2.51	2.55	2.58	2.27	2.30	2.33	1.98	2.01	2.04	1.77	1.79	1.82
2025	2.52	2.58	2.63	2.39	2.44	2.50	2.22	2.27	2.32	2.08	2.13	2.17
2030	2.55	2.63	2.71	2.48	2.56	2.64	2.38	2.46	2.53	2.30	2.37	2.44

Table 5.8 shows the Palma ratio in SCRO7 where the tax revenues are recycled to the low-income subgroup only, and the abatement costs are paid by the high-income subgroup only. The Palma ratio shown in Table 5.8 is lower than that in Table 5.7, which implies that recycling the tax revenues to the low-income subgroup rather than evenly to the household is beneficial to reducing the income inequality further. This finding complies with Grottera, Pereira et al. (2017) who empirically found that recycling the tax revenues to the lower income class was the one which contributed the most to the reduction of the income inequality in Brazil.

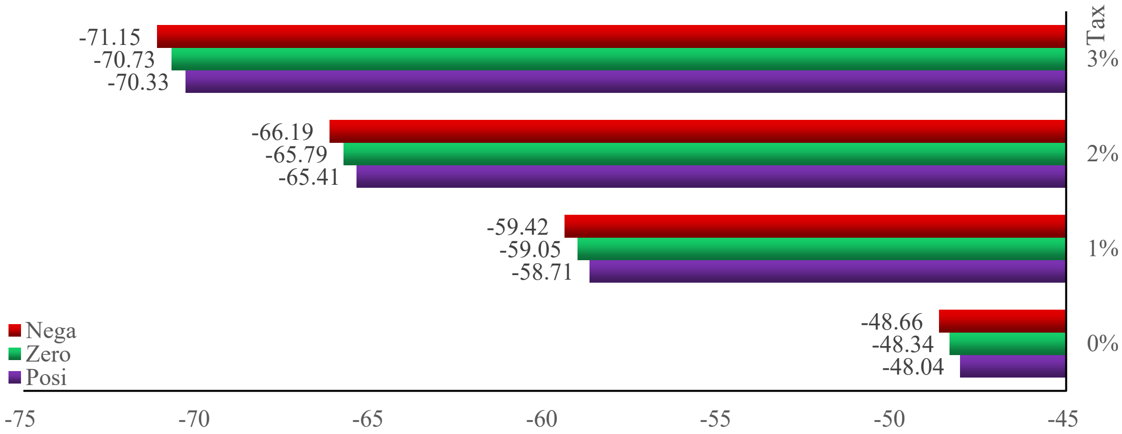


Fig. 5.5 The Relative Utility (RU) in SCRO7 (Unit: 10^9 CNY)

Fig. 5.5 shows the RU in SCRO7 where the tax revenues are recycled to the low-income subgroup only. The absolute value of the RU in the tax scenarios of Fig. 5.5 is lower than that in Fig. 5.4. This result implies that at the same absolute income, recycling the revenues to the low-income subgroup will induce the lowest inequality condition and thus the lowest absolute value of the RU. On the assumption of recycling the tax revenues to the low-income household only, Table A5.3 and Fig. A5.3 in Appendix A show the Palma ratio and RU in SCRO8 where the abatements costs are proportional to the income; Table A5.4 and Fig. A5.4 in Appendix A show the Palma ratio and RU in SCRO9 where the abatements costs are independent from the income.

Table 5.9 The Palma Ratio in SCRO10

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.26	2.27	2.28	1.89	1.90	1.91	1.61	1.62	1.63
2020	2.51	2.55	2.58	2.28	2.31	2.34	2.00	2.03	2.06	1.79	1.82	1.85
2025	2.52	2.58	2.63	2.40	2.46	2.51	2.24	2.29	2.34	2.10	2.15	2.20
2030	2.55	2.63	2.71	2.49	2.57	2.65	2.40	2.48	2.55	2.32	2.40	2.47

Table 5.9 shows the Palma ratio in SCRO10 where the tax revenues are recycled to the enterprise, and the abatement costs are paid by the high-income subgroup only. Recycling the revenues to the enterprise will deteriorate the inequality condition, compared to the case that the household receives the revenues. This is because the high-income subgroup will gain disproportionally more revenues, but the low-income subgroup will gain disproportionally less revenues under this recycling assumption. Although the data in Table 5.9 are roughly equal to that in Table 5.4, the Palma ratio in Table 5.9 is slightly larger than that in Table 5.4 in four decimals. Hence, Table 5.9 implies that recycling the revenues to the enterprise will induce the largest inequality condition among the designed recycling policies. This finding complies with Caron, Cohen et al. (2018), Gonzalez (2012) and Jorgenson, Goettle et al. (2018) who showed that using the tax revenues for capital formulation was regressive and thus increased the inequality.

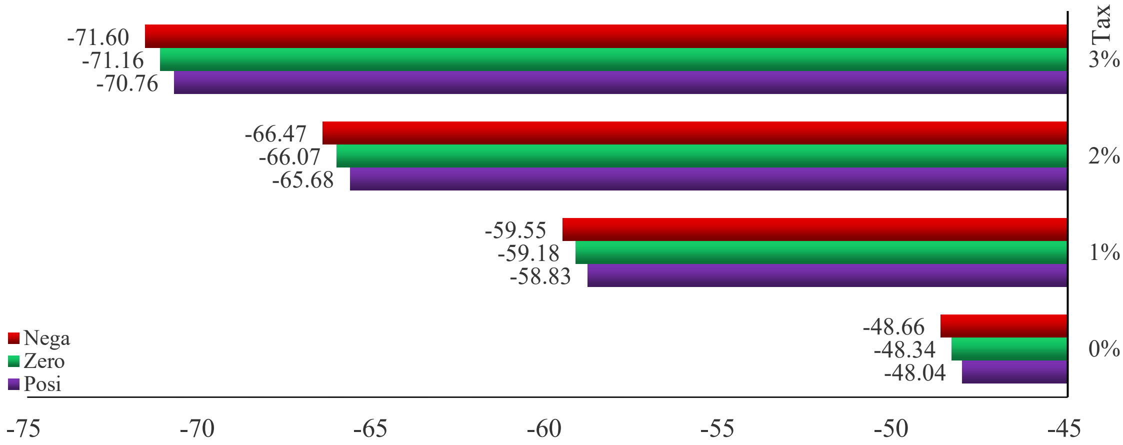


Fig. 5.6 The Relative Utility (RU) in SCRO10 (Unit: 10^9 CNY)

Fig. 5.6 shows the RU in SCRO10 where the tax revenues are recycled to the enterprise. The absolute value of the RU in the tax scenarios of Fig. 5.6 is the largest, compared to Fig. 5.1–5.5. On the assumption of recycling the tax revenues to the enterprise, Table A5.5 and Fig. A5.5 in Appendix A show the Palma ratio and RU in SCRO11 where the abatements costs are proportional to the income; Table A5.6 and Fig. A5.6 in Appendix A show the Palma ratio and RU in SCRO12 where the abatements costs are independent from the income.

Table 5.10 The Household Welfare Loss under the Tax Recycling Policies (Unit: 10^{12} CNY)

Tax	1%			2%			3%		
Recipient	GOV	HLD	EPS	GOV	HLD	EPS	GOV	HLD	EPS
2015	9.798	9.790	9.802	13.514	13.501	13.521	15.532	15.516	15.541
2020	18.323	18.310	18.328	24.902	24.884	24.911	28.392	28.370	28.405
2025	25.998	25.977	26.006	36.767	36.737	36.782	42.803	42.767	42.824
2030	35.019	34.988	35.031	51.702	51.654	51.725	61.654	61.595	61.687

Note: "GOV" and "EPS" stand for the revenues recycled to the government and enterprise; "HLD" refers to the revenues recycled evenly to the household.

Table 5.10 shows the household welfare loss induced by the revenue recycling policies. Recycling the revenues to the household will induce the lowest amount of the welfare loss under the carbon tax. Noticeably, the differences of the welfare loss under the recycling policies are quite minimal (less than 1%). This is because the RU defined in Eq. (5.26) has minimal impacts on the net welfare. Hence, the sharing of the climate damages or abatement costs, which affects the RU only, will have almost no effects on the welfare loss induced by the carbon tax.

Table 5.11 The RGDP Loss under the Tax Recycling Policies (Unit: 10^{12} CNY)

Tax	1%			2%			3%		
Recipient	GOV	HLD	EPS	GOV	HLD	EPS	GOV	HLD	EPS
2015	24.501	24.504	24.505	33.863	33.869	33.872	39.021	39.029	39.034
2020	39.792	39.797	39.797	54.070	54.079	54.081	61.705	61.716	61.720
2025	48.464	48.471	48.470	68.383	68.394	68.397	79.578	79.593	79.599
2030	56.135	56.143	56.142	82.611	82.626	82.630	98.381	98.402	98.409

Table 5.11 shows the effect of the revenue recycling policies on the real GDP (RGDP) loss over time. Like the household welfare loss, the RGDP loss is also minimally affected by recycling the tax

revenues. According to Table 5.11, the government policy will induce the lowest amount of the RGDP loss, which implies that recycling the revenues to the government is the most efficient way to use the tax revenues at the country level.

Results of the Sensitivity Analysis

Table 5.12 The RU Change in the Baseline Scenario When ξ is Positive

$\Delta\gamma_1$ or $\Delta\gamma_2$	-50%	-40%	-30%	-20%	-10%
ΔRU by $\Delta\gamma_1$	1.80%	1.42%	1.05%	0.69%	0.34%
ΔRU by $\Delta\gamma_2$	UND	26156.70%	2067.88%	530.96%	136.48%
$\Delta\gamma_1$ or $\Delta\gamma_2$	10%	20%	30%	40%	50%
ΔRU by $\Delta\gamma_1$	-0.33%	-0.66%	-0.98%	-1.28%	-1.58%
ΔRU by $\Delta\gamma_2$	-54.45%	-78.15%	-89.10%	-94.40%	-97.05%

Note: UND means undefined.

Table 5.12 shows the RU percentage change influenced by the parametric values of $\Delta\gamma_1$ or $\Delta\gamma_2$ in the baseline scenario when the income elasticity of damage (ξ) is positive. According to Table 5.12, the relative utility is quite insensitive to γ_1, which means that the RU is quite robust to the parametric uncertainties of γ_1. Noticeably, the changes of γ_1 is negatively correlated with the absolute value of the RU. In contrast, the RU is quite sensitive to the parametric uncertainties of γ_2. If γ_2 changes by -40%, the absolute value of γ_2 will increase by 26156.70%. However, even if the RU has changed by that large amount, its impact on the net welfare is still very small, and thus the variation of the RU will not change the optimum condition of the model equilibrium. Table A5.7–A5.10 in Appendix A show the results of the sensitivity analysis under the different assumptions of the abatement costs, climate damages, and targeted recipients of the revenues in the tax scenarios. Similar findings could be found in Table A5.7–A5.10, compared to Table 5.12.

Discussion

This chapter empirically shows that the income elasticity of damage (ξ) affects the inequality condition. The negative value of ξ means that the distribution of the income (equality condition) is disproportional to the income. Consequently, the inequality condition will be higher than the case where ξ is positive or zero. This finding is compatible with the argument that the poor were often disproportionally exposed to the damages relating to the climate change, according to Winsemius, Jongman et al. (2018) whose research was based on the survey data in 52 countries. Hence, the climate change would exacerbate the inequality condition, according to Beck (2010) who remapped the social inequality at the age of the climate change.

If the abatement costs are independent from the income, the carbon tax will increase the inequality condition. This finding corresponds to the previous research arguing that a carbon tax would usually increase the inequality condition because of the rising energy prices, according to Markkanen and Anger-Kraavi (2019) who synthesised the evidence of the inequality impacts of climate policies in the literature. Specifically, Freitas, Ribeiro et al. (2016) analysed the economic and distributional effects of the Brazilian emission taxation, concluding that the tax increased the inequality condition in Brazil.

A decrease in the income, caused by the increase of the tax rate, always results in an increase in the absolute value of the relative utility even if the tax decreases the inequality condition. This finding complies with Clark, Frijters et al. (2008) who reviewed the evidence on the relative income from the well-being literature, arguing for the positive correlations between the individual income and well-being irrespective of the negative relation between the happiness and others' income. This finding implies that compared to the inequality condition, the absolute income has a more influential impact on the relative utility.

Keeping the tax revenues in the governmental budget is equivalent to the case with no revenue recycling in the literature. According to Wang, Hubacek et al. (2019) who used a multi-regional input-output model to analyse the distributional impacts of the carbon pricing in China, the carbon tax was regressive without revenue recycling; the regressivity means the burden of the tax on the poor was higher than that on the rich. Conversely, Klenert and Mattauch (2016) analysed the distributional effects of the carbon tax reform to conclude that the carbon tax could decrease the inequality condition if the revenues were recycled as uniform lump-sum transfers.

Recycling the tax revenues to the household will induce the lowest inequality condition in comparison with the recycling policies to the other recipients. This finding is compatible with Montenegro, Lekavicius et al. (2019) who used a multi-regional CGE to study the challenges and opportunities of the EU climate policies, empirically showing that redistributing the revenues from the carbon certificates decreased the income inequality. This is because the poor derived a higher share of their income from the governmental income redistribution than the rich (Montenegro, Lekavicius et al. 2019). In summary, recycling the tax revenues to the household could relieve the inequality condition, compared to keeping the tax revenues in the governmental budget.

Recycling the revenues to the low-income subgroup only will induce a more equitable condition, compared to the policy where the household receives the tax revenues evenly. By providing the best means for sheltering the poorest, recycling the revenues to the household was the most equitable way to use the tax revenues, according to Jorgenson, Goettle et al. (2018) who employed an intertemporal CGE model to study the welfare consequences of the carbon taxation. Similarly, Berry (2019) using a microsimulation model to study the distributional effects of the French carbon tax, indicating that targeting the revenue recycling at the low-income household was the cheapest option to offset the regressivity of the carbon tax in France.

There is a tradeoff between the equity and efficiency among the revenue recycling policies, and the tradeoff could be also found in Caron, Cohen et al. (2018) who used a CGE model to explore the effects of the US economy-wide carbon taxes. In this chapter, the most equitable policy is recycling the revenues to the household, whilst the most efficient policy is keeping the revenues in the governmental budget as this policy will induce the lowest amount of the RGDP loss. This finding is quite different from Caron, Cohen et al. (2018), Gonzalez (2012), and Jorgenson, Goettle et al. (2018) who showed that capital formulation was the most efficient to use the tax revenues. The result difference lies in the assumption of the capital tax: in the previous studies, the capital tax was endogenously determined; in this chapter, it is exogenously given by 2015 China Input-Output Table and assumed to change dynamically from the 2015 data. Hence, in this chapter, the revenues are recycled to the enterprise as an increase of its income.

The sensitivity analysis shows the relative utility (RU) defined in this chapter is insensitive to the parametric value of the weight of relative income (γ_1) but quite sensitive to the rate at which the RU falls as the income rises (γ_2). This finding implies that the RU will be seriously affected by the parametric uncertainties of γ_2. Hence, the definition of the RU in this chapter needs to be improved. Future potential research may define the RU in a way that its value is robust to the given values of both γ_1 and γ_2.

As the relative utility, affected by the inequality impacts, only slightly influences the total welfare, the optimum condition of the technical model (defined in the previous chapter) does not change. The model equilibrium changes very minimal if the inequality impacts are considered. Hence, the carbon emissions and carbon intensity will be almost the same irrespective of the inequality impacts. Whether the carbon tax will help China meet the INDC target remains unchanged in this chapter, compared to the previous chapter.

The Tinbergen Rule implies that one policy instrument per target is needed (Braathen 2007). As the previous chapters have already included the ancillary and primary benefits and technical impacts in the policy evaluation framework, the simulated carbon tax may not reveal the net inequality impacts in this chapter. To reduce the inequality impacts, an addition policy instrument, like subsidies for the poor, needs to be implemented as a complementary policy of the carbon tax.

Policy Implications

The inequality condition is not a significant factor that influences the policy effects of the carbon tax because the relative utility is quite small compared to the absolute utility. The inequality impacts of the carbon tax are affected by the assumption of the distribution of the climate damages, payment of the abatement costs, and recipients of the tax revenues.

Conclusion

This chapter empirically shows that if the climate damages are assumed to be positively related to the income, the inequality condition will be the lowest under the implementation of the carbon tax. If the climate damages become independent from the income, the low-income subgroup will suffer more welfare loss, and thus the inequality condition will increase. If the climate damages are negatively correlated with the income, the low-income subgroup will suffer the largest amount of the welfare loss, and thus the inequality condition will be the highest.

The abatement costs can be paid by the high-income subgroup only, proportionally to or independently from the income. The inequality condition will be the lowest if the high-income subgroup pays the abatement costs and will be the highest if the abatement costs are independent from the income. The carbon tax is progressive if the abatement costs are paid by the high-income subgroup; it is neutral if the abatement costs are proportional to the income; it is regressive if the abatement costs are independent from the income.

Recycling the tax revenues has a profound effect on the inequality condition and relative utility. Among the recycling policies, the inequality condition and absolute value of the relative utility will be the lowest if the tax revenues are recycled to the low-income subgroup only. On the contrary, recycling the revenues to the enterprise will induce the highest inequality condition and absolute value of the relative utility. Nevertheless, the recycling policies will only minimally (less than 1%) affect the household welfare loss and real GDP loss, induced by the carbon tax.

The relative utility is mainly determined by the absolute income even though the income inequality does have an impact on it. As the tax rate increases, the absolute value of the relative utility will always increase even if the increasing tax rate could result in less inequality. This is because as the tax rate increases, the absolute income of each household subgroup will always decrease irrespective of the income distribution within the household.

The sensitivity analysis shows that the relative utility is quite robust to the parametric values of γ_1 but quite sensitive to the parametric values of γ_2. As the relative utility is quite minimal compared to the total welfare, using the net welfare (the total welfare minus the relative utility) instead of the total welfare as the optimum condition almost has no impacts on the policy effects of the carbon tax. Even if γ_2 may significantly change the relative utility, the variation of the relative utility is still very minimal compared to the total welfare. Hence, I conclude that considering the inequality impacts, the evaluation on the policy effects of the carbon tax in this chapter is robust despite that the relative utility is sensitive to γ_2.

Chapter 6: The Urbanisation Impacts on the Carbon Tax

Introduction

Since the Reform and Opening-up in 1978, China has been experiencing rapid urbanisation. The urbanisation rate (the percentage of the urban population in the total population) increased from 17.9% in 1978 to 51.27% in 2011 with an annual growth rate of 1.02% on average (Wang, Fang et al. 2014). This trend would continue in the future particularly in the western and central regions of China (Wang 2014). The rapid urbanisation poses tremendous socioeconomic challenges for the sustainable development in China (Wang, Fang et al. 2014). One of the challenges is the expanding anthropogenic emissions accompanied by the urbanisation.

The urbanisation impacts on carbon emissions are complicated as urbanisation changes economic production, lifestyles, and land use types (Xu, Dong et al. 2018). On the one hand, urbanisation-induced industrialisation results in the intensive use of energy, which increases carbon emissions; on the other hand, geographical concentration may enhance the efficiency of energy use, which decreases carbon emissions. Previous researchers have documented the following four types of urbanisation impacts (Xu, Dong et al. 2018): (1) the urbanisation positively affected the carbon emissions in the Middle East and North African countries, implied by the panel model over the period 1980–2009 (Al-mulali, Fereidouni et al. 2013); (2) negative impacts were found in China during 1978–2010, implied by the cointegration and Granger causality test (Zhao and Chen 2013); (3) the urbanisation had no significant impacts in 32 Chinese cities during 1999–2011, implied by the cointegration analysis (Ji, Wu et al. 2013); (4) the urbanisation impacts on the carbon emissions took the form of an inverse U-shaped curve in China during 1979–2009, implied by the decomposition of the urbanisation shocks (Dong and Yuan 2011). Although previous researchers studied how the Chinese urbanisation affected the historical emissions, the projected urbanisation impacts during 2015–2030 remain to be researched in China.

Urbanisation affects energy consumption because cities are the main contributors to fossil-fuel energy consumption worldwide (Zhao and Zhang 2018). Hence, urbanisation is likely to increase energy consumption. For example, a one-way positive causal relationship existed from the urbanisation to the energy consumption, according to Wang, Fang et al. (2014) who performed a panel data analysis on 30 Chinese provinces during 1995 to 2011. Conversely, urbanisation could also reduce energy consumption because it saves energy use in transport. For example, the urbanisation was empirically found to have a positive effect on reducing the residential energy use in the 12 transition economies during 1995–2013, according to Pablo-Romero, Sanchez-Braza et al. (2019) who tested the environmental Kuznets curve (EKC) hypothesis. Some researchers analysed both the positive and negative impacts of urbanisation on energy consumption. For example, Wang (2014) investigated the impacts of the Chinese urbanisation on the energy consumption through a time-series analysis, concluding that the urbanisation slowed per capita residential energy consumption growth, but it had a greater promotional impact on the energy consumption growth.

In addition to the environmental impacts, the rapid expansion of urban areas could generate profound economic impacts. Urbanisation both has positive and negative impacts on the economy, including the development of commercial activities and creation of new jobs; bridging the wealth gap; access to new technologies and activities; infrastructure development (Dociu and Dunarintu 2012). Deng, Huang et al. (2015) mapped the Chinese urban expansion in 2001–2013, concluding that the urbanisation created positive externalities through technological innovation and shared information, and generated negative externalities including public insecurity and social inequality. Wu, Fisher et al. (2011) used a multiple-equation empirical model to explore the US county data, concluding that the urbanisation influenced the costs and profits of farming.

In summary, previous research shows that urbanisation affects energy consumption, carbon emissions, and economic growth altogether. Studies that omit the urbanisation impacts on any variable mentioned above tend to be biased owing to the omission of an explanatory variable. For example, Zhao and Zhang (2018) only focused on the bidirectional impacts of the urbanisation on the energy consumption in China during 1980–2010. As Zhao and Zhang (2018) only implicitly studied the energy-related emissions affected by the urbanisation but excluded the direct urbanisation impacts on the emissions, their results might be biased owing to the fact that the urbanisation could affect the emissions directly (Xu, Dong et al. 2018). In contrast, Al-mulali, Sab et al. (2012) and Wang, Fang et al. (2014) neglected the urbanisation impacts on the economic growth. With the omission of an influential explanatory variable, these studies may not give full understanding of the urbanisation impacts. In comparison with these studies, Zhang, Yi et al. (2015) fully studied the relation between the urbanisation and its three influential factors. Hence, their results could be much more trustworthy compared to the aforementioned studies.

Hence, in this chapter, I have referred to Zhang, Yi et al. (2015) who used an autoregressive distributed lag (ARDL) model to investigate the impacts of the urbanisation in Beijing during 1980–2013. More specifically, an ARDL model is used in this chapter to study the interrelations among these variables during 1980–2014 in China instead of Beijing, which was the target area in Zhang, Yi et al. (2015). I assume that the historical ARDL interrelations will remain unchanged in 2015–2030. Based on the projected urbanisation data given by UN (2018), the projected urbanisation impacts are inputted into the inequality model, defined in the previous chapter, and the new model is named as the urbanisation model in this chapter. The result comparison between the two models will reveal the net impacts of the projected rapid Chinese urbanisation on the policy effects of the carbon tax.

This chapter contributes to the literature by introducing the urbanisation impacts into the CGE policy evaluation framework. To my best knowledge, very few studies have attempted to identify whether urbanisation is an influential factor of climate policies. Neglecting the urbanisation impacts is likely to induce the biased evaluation of climate policies because the structural transition in urban population has a significant influence on the efforts to mitigate carbon emissions (Wang, Wu et al. 2019). Therefore, it is important that the urbanisation impacts should be modelled in the policy evaluation framework.

Data

The coefficients of the ARDL model are calculated using the historical (1980–2014) data of the four variables to be researched, namely the urbanisation rate, carbon emissions, GDP, and energy consumption. The historical urbanisation data are from 2018 World Urbanisation Prospects (WUP) by United Nations (UN). The carbon emission data are from the index of "CO_2 Emissions (kt)" in World Development Indicators (WDI) by World Bank (WB). The GDP data are from the index of "GDP (constant 2010 US$)" in WDI by WB. The energy consumption data are from the index of "Total Energy Consumption" in China Energy Statistical Yearbook by NBS (2016). All the data have been transformed into their logarithm expressions to interpret the relative changes of the variables.

The projected urbanisation rate data are also from 2018 WUP.[1] By comparison, Sun, Zhou et al. (2017) predicted the urbanisation in China from 2016 to 2030 based on the fertility, mortality, and natural growth rate data.

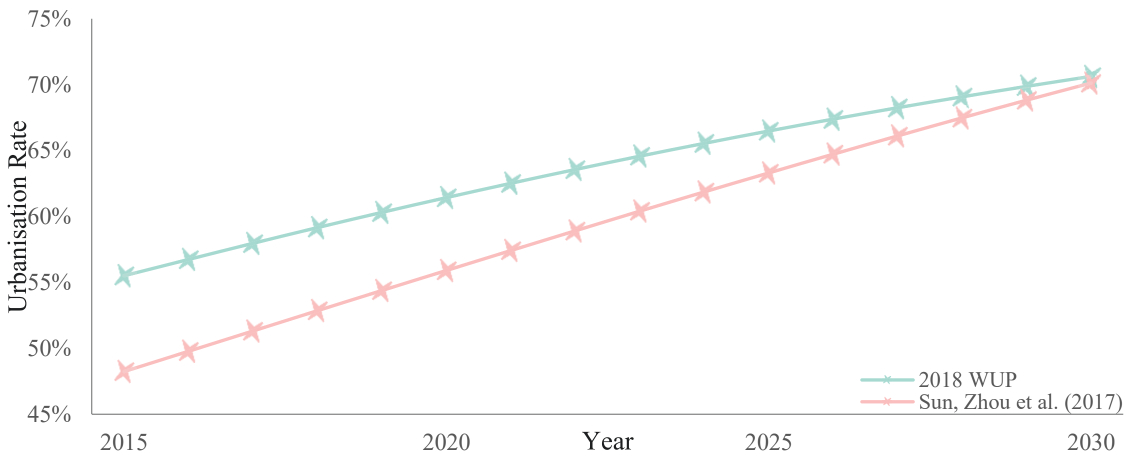


Fig. 6.1 The Projected Urbanisation Rate in China

Fig. 6.1 depicts the projected urbanisation rate by 2018 WUP in UN (2018) and Sun, Zhou et al. (2017). The urbanisation rate in China will continue to rise in both projections, but Sun, Zhou et al.

[1] According to Hsieh, S. C. (2014). "Analyzing urbanization data using rural-urban interaction model and logistic growth model." Computers Environment and Urban Systems **45**: 89-100., UN is the only institution that produces the projections of the urban and rural population growth worldwide in its annual publication "World Urbanisation Prospect". Although the WUP data have been broadly applied in the literature, the data tend to overlook the regional socioeconomic conditions.

(2017) projected the lower urbanisation rate with the larger increase rate compared to UN (2018). In 2030, the urbanisation rate in both projections will be very similar, which implies that there will be 70% of the Chinese population living in the urban area in 2030. As Sun, Zhou et al. (2017) employed a logistic curve to predict the urbanisation rate, their results were volatile owing to the model specification errors or unexplained residuals. Hence, the results in Sun, Zhou et al. (2017) would have been changed if a different model had been employed. For example, Gu, Guan et al. (2017) used a dynamic system model to project the Chinese urbanisation, and their results varied in five different scenarios. Considering its widespread acceptance and applicability, the 2018 WUP data are adopted in this chapter, even though the data might overlook the unique socioeconomic conditions in China.

Table 6.1 The Projected Urbanisation Rate in China

Year	Rate	Year	Rate	Year	Rate	Year	Rate
2015	55.50%	2019	60.31%	2023	64.57%	2027	68.25%
2016	56.74%	2020	61.43%	2024	65.54%	2028	69.07%
2017	57.96%	2021	62.51%	2025	66.48%	2029	69.87%
2018	59.15%	2022	63.56%	2026	67.38%	2030	70.63%

Source: UN (2018)

Table 6.1 specifies the 2018 WUP data shown in Fig. 6.1. According to Table 6.1, the urbanisation in China was projected to grow continuously over the research period. However, the urbanisation growth will decelerate, and the urbanisation rate will exceed 70% in 2030.

Method

Because an ARDL model provides reliable results when the variables are in the mixed orders of the stationarity (Kalmaz and Kirikkaleli 2019), it has become very popular to analyse the cointegration relations among economic time series in the literature. However, the cointegration relations need to be tested in case that the model becomes a spurious regression. The cointegration relations are identified based on unit root tests which reveal whether a time-series is stationary.

In the literature, the most commonly used unit root test is the Augmented Dickey-Fuller (ADF) test, also known as the standardized panel unit root test, based on the deviations from the estimated factors (Pesaran 2007). The null hypothesis of an ADF test is that a unit root exists in the time series, while the alternative hypothesis indicates that there is no unit root, and the time series is stationary. The results of an ADF test were proved to be robust to the different lag specifications and test misspecifications (Hooker 1993). However, an ADF test was proved to be biased when the selection of the lag length is too small or large (Phillips and Perron 1988, Schwert 1989). Therefore, I will use the other types of the unit root tests that have been developed. For example, proposed by Phillips and Perron (1988), the PP test is nonparametric with respect to nuisance parameters and thereby allows for a very wide class of weakly dependent and possibly heterogeneously distributed data. Choi and Chung (1995) empirically proved that for the data with low sampling frequency, a PP test is more powerful than an

ADF test in finite samples. As the sample size in this chapter is small, the results of a PP test could be more reliable than that of an ADF test.

Based on unit root tests, panel cointegration tests strive to provide more reliable results in testing the cointegration presence relative to those obtained by individual tests (Mitic, Ivanovic et al. 2017). The most frequently used panel cointegration test is the Engle-Granger (EG) cointegration test, put forward by Engle and Granger (1987). The EG test was derived from the basic idea that two nonstationary time series are cointegrated if there is a stationary linear combination of them, from which the residuals are also stationary (Mitic, Ivanovic et al. 2017). The null hypothesis of the EG test is that there is no long-term cointegration relationship. The existence of a cointegration relationship is determined by the F statistics larger than the corresponding critical value.

After the existence of the cointegration relationships is confirmed, an autoregressive distributed lag (ARDL) model is defined according to Pesaran, Shin et al. (2001). In this chapter, the ARDL model is constructed using the HAC (Newey-West) coefficient covariance matrix as the HAC method is more robust than the ordinary method. Eq. (6.1) shows the long-term ARDL model where the carbon emissions are the dependent variable. Similar equations can be written when the energy consumption or GDP is the dependent variable. Because this chapter is targeted at the urbanisation impact, the urbanisation rate is only introduced as an independent variable in the ARDL model.

$$E_t = \gamma_0 + \sum_{k=1}^{L1} \gamma_{1k} E_{t-k} + \sum_{k=0}^{L2} \gamma_{2k} EC_{t-k} + \sum_{k=0}^{L3} \gamma_{3k} UR_{t-k} + \sum_{k=0}^{L4} \gamma_{4k} GDP_{t-k} + \varepsilon_t \quad (6.1)$$

In Eq. (6.1), E_t refers to the total carbon emissions in Year t. EC_{t-k}, UR_{t-k}, and GDP_{t-k} stand for the total energy consumption, urbanisation rate, and GDP in Year t-k respectively. L_1 , L_2 , L_3 , L_4 are the optimal lagged orders to be selected by the Schwarz Information Criterion (SIC). The maximum lag for all the variables is three owing to the constraint by the small sample size. ε_t refers to the residual term in Year t; presumably, it is a white noise showing the independence and equal variance. γ_0, γ_{1k}, γ_{2k}, γ_{3k}, γ_{4k} are all the regression coefficients, and γ_0 is the intercept. As all the variables are taken into their logarithm forms, the coefficients denote the elasticities.

To check the robustness of the ARDL model, I have performed the residual diagnostic tests: a White test to check the heteroskedasticity; a Breusch-Godfrey Serial Correlation LM test to check the autocorrelation; a histogram to check the normality. The variance inflation factor (VIF) is used to test the multicollinearity, whilst a recursive residual plot is used to test the model stability.

Once the urbanisation impacts are captured by the ARDL model, Eq. (6.2) is used to model the impact on the policy effects of the carbon tax, assuming that the historical ARDL relationships will remain unchanged in 2015–2030. The urbanisation impacts on the carbon emissions and real GDP (RGDP) are also assumed to be equal across the sectors and household. Noticeably, the unit impact of the urbanisation on the historical GDP is deemed to have an equal impact on the historical RGDP.

$$\begin{cases} E_{it}^{ur} = E_{it} * (1 + ur_t^E) \\ SGDP_{it}^{ur} = SGDP_{it} * (1 + ur_t^{GDP}) \\ EC_{it}^{ur} = EC_{it} * (1 + ur_t^{EC}) \end{cases} \tag{6.2}$$

In Eq. (6.2), E_{it}^{ur}, $SGDP_{it}^{ur}$, and EC_{it}^{ur} refer to the revised carbon emissions, sectoral output, and energy consumption when the net urbanisation impacts are considered. ur_t^E, ur_t^{GDP}, and ur_t^{EC} are the urbanisation impact indicators of the carbon emissions, GDP, and energy consumption respectively.

In this chapter, the results of the urbanisation model, which considers the urbanisation impacts quantified by the ARDL model, are compared with the results of the inequality model defined in the previous chapter. Performed by the relative changes of the socioeconomic and emission indexes, the comparison analysis will reveal to what extent the projected Chinese urbanisation will influence the policy effects of the carbon tax.

Results of the ARDL Model

In Table A6.1 in Appendix A, the determination of the intercept and trend in the unit root tests is based on the information criteria to minimise the information loss. The first-order difference of E_t does not have a unit root according to the PP test, but the ADF test shows an opposite result. I conservatively believe that E_t is integrated for order two as both tests show that the second-order difference is stationary. Similarly, Table A6.1 implies that GDP_t is integrated for order one, whilst EC_t and UR_t are integrated for order two.

Table 6.2 The Results of the EG Cointegration Tests

Variable Form	Dependent Variable	Tau-Statistic	P-value	Z-Statistic	P-value
Level	E_t	-4.13	0.0892	-31.03	0.0062**
	EC_t	-4.09	0.0949	-16.27	0.3300
	GDP_t	-5.97	0.0019**	-55.64	<0.0001**
Differenced	$\Delta^2 E_t$	-6.67	0.0004**	-90.63	<0.0001**
	$\Delta^2 EC_t$	-7.54	<0.0001**	-41.45	<0.0001**
	$\Delta^2 GDP_t$	-4.41	0.0555	-43.29	<0.0001**

Note：Δ^2 denotes the second-order difference; ** denotes statistical significance at the 5% level.

Table 6.2 presents the EG test results at the level and differenced dependent variables. When the dependent variable is $\Delta^2 E_t$, the Z-Statistic is statistically significant, whilst the Tau-Statistic is statistically insignificant. According to Mackinnon (1996), when the sample size is very small, the differences between the finite-sample and asymptotic distributions are quite small for the Tau-Statistics but very large for the Z-Statistics. As the sample size in this chapter is small, the results of the Tau-Statistics are more persuasive. The EG test results for the differenced $\Delta^2 E_t$ show that both the Tau-Statistics and Z-Statistics are significant at the 5% level, which means that the null hypothesis of the EG test is not accepted. Hence, Table 6.2 implies that when $\Delta^2 E_t$ is the dependent variable, the differenced EG test confirms the existence of a cointegration relationship. Table 6.2 shows a similar implication in the EG test when $\Delta^2 EC_t$ is the dependent variable. In contrast, if GDP_t is the dependent variable, the level EG test confirms that a cointegration relationship exists.

As three cointegration relationships are confirmed by the EG test, three ARDL models are constructed correspondingly, and the results are shown in Table 6.3.

Table 6.3 The Results of the ARDL Models

Dependent Variable	Independent Variable	Coefficient	P-value
$\Delta^2 E_t$	$\Delta^2 E_{t-1}$	-0.43	<0.0001***
	$\Delta^2 EC_t$	1.01	0.0002***
	$\Delta^2 EC_{t-1}$	0.47	0.0052***
	ΔGDP_t	0.18	0.0772*
	$\Delta^2 UR_t$	3.51	0.0083***
	C	-0.017	0.1152
$\Delta^2 EC_t$	$\Delta^2 EC_{t-1}$	-0.28	0.0170**
	$\Delta^2 E_t$	0.58	<0.0001***
	$\Delta^2 E_{t-1}$	0.35	0.0110**
	ΔGDP_t	0.0031	0.8946
	$\Delta^2 UR_t$	-0.59	0.6690
GDP_t	GDP_{t-1}	1.11	<0.0001***
	GDP_{t-2}	-0.59	<0.0001***
	E_t	0.31	0.0280**
	EC_t	-0.35	0.0452**
	UR_t	1.59	0.0010***
	C	7.3851	0.0001***

Note：*denotes statistical significance at the 10% level; **denotes significance at the 5% level; *** denotes significance at the 1% level

Table 6.3 displays the coefficients and their significance levels in the ARDL models. If $\Delta^2 E_t$ is the dependent variable, the independent variables have positive impacts on it except for its lagged term. The coefficient of $\Delta^2 UR_t$ is statistically significant at the 1% level, and it means that when $\Delta^2 UR_t$ increases (decreases) by 1%, $\Delta^2 E_t$ will increase (decrease) by 3.51%. When $\Delta^2 EC_t$ is the dependent variable, the coefficient of $\Delta^2 UR_t$ is not statistically significant even at the 10% level, implying that the urbanisation does not have a significant impact on the energy consumption. When GDP_t is the dependent variable, the coefficient of UR_t is statistically significant at the 1% level.

When GDP_t is the dependent variable, severe problems of the heteroskedasticity, autocorrelation, and multicollinearity exist in the ARDL model. Hence, I have made the first-order difference of the variables and rerun the ARDL model. As the Tau-Statistic and Z-Statistic are both statistically significant at the 5% level, I conclude that the cointegration relationship is not spurious.

Table 6.4 The Result of the ARDL Model (Dependent Variable: ΔGDP_t)

Independent Variable	Coefficient	P-value
ΔGDP_{t-1}	0.68	0.0001***
ΔGDP_{t-2}	-0.37	0.0342**
ΔE_t	0.25	0.2804
ΔEC_t	-0.19	0.5291
ΔUR_t	2.10	0.0005***

Table 6.4 shows the ARDL model results when the dependent variable is the first-order differenced GDP. In Table 6.4, the coefficient of ΔUR_t is statistically significant at the 1% level, and it means that if ΔUR_t increases (decreases) by 1%, ΔGDP_t will increase (decrease) by 2.10%.

In Appendix A, Table A6.2 and A6.3 display the results of the robust tests to determine whether the simulated ARDL models violate the embedded statistical assumptions. Table A6.2 shows that, for all the three ARDL models, the F-Statistics of the White tests are not statistically significant, implying that the null hypotheses of the residual equal variances are accepted. Similarly, the LM test's null hypotheses that the residuals do not have serial correlations are accepted. Table A6.3 shows the VIFs of the independent variables are all less than 10 in the $\Delta^2 E_t$ and $\Delta^2 EC_t$ models, indicating that there are no severe multicollinearity problems in these two models. However, in the ΔGDP_t model, the multicollinearity can be a serious problem. Although the multicollinearity may inflate the variations of the coefficients, the estimated coefficients are still unbiased. As the coefficient of ΔUR_t is statistically significant, I conclude that the multicollinearity has not generated severe adverse consequences on the study of the urbanisation impacts on the GDP in this chapter.

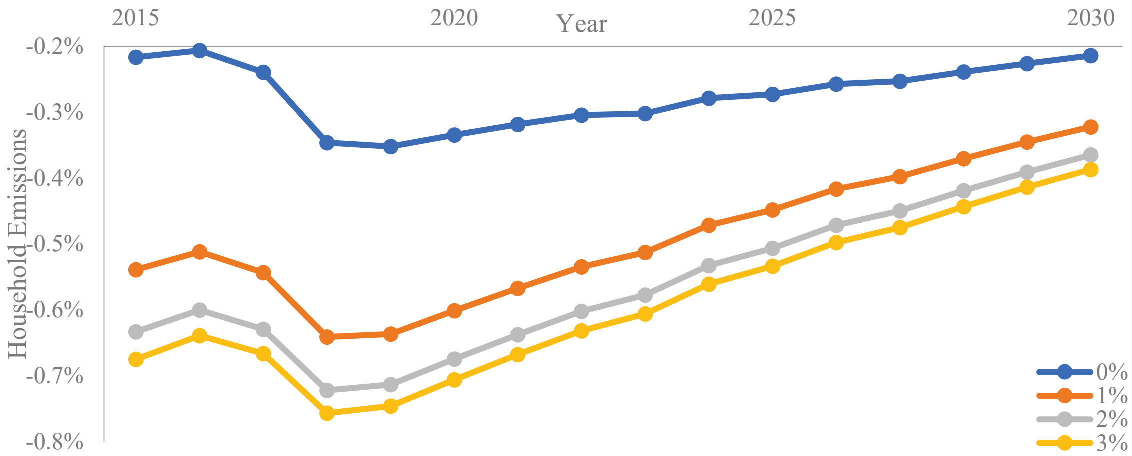
In Appendix A, Fig. A6.1–A6.3 show that the residual terms approximately comply with the normality assumption. Fig. A6.4–A6.6 show that in each ARDL model, there are some data points lying outside the two-standard-error ranges, implying that these data points may lay undue influences on the model results. However, as most of the data points lie within the two-standard-error ranges, I conclude that the stability assumption is roughly met.

Table 6.5 The Projected Impacts of the Urbanisation on the CO_2 Emissions and RGDP

Year	CO_2	RGDP	Year	CO_2	RGDP	Year	CO_2	RGDP
2015	-0.22%	4.75%	2021	-0.32%	3.67%	2027	-0.25%	2.68%
2016	-0.21%	4.62%	2022	-0.30%	3.49%	2028	-0.24%	2.53%
2017	-0.24%	4.48%	2023	-0.30%	3.31%	2029	-0.23%	2.40%
2018	-0.35%	4.27%	2024	-0.28%	3.14%	2030	-0.21%	2.27%
2019	-0.35%	4.06%	2025	-0.27%	2.98%			
2020	-0.33%	3.86%	2026	-0.26%	2.83%			

According to the projected urbanisation data in 2018 WUP by UN (2018), the projected percentage impacts of the Chinese urbanisation during 2015–2030 are shown in Table 6.5. The urbanisation will have a consistently negative impact on the carbon emissions. In contrast, the urbanisation will positively affect the RGDP, but the impact will attenuate over time.

Result Comparison between the Inequality and Urbanisation Model



Note: 0% refers to the baseline scenario; 1%, 2%, and 3% denote the tax rates

Fig. 6.2 The Urbanisation Impact on the Household Emissions

Fig. 6.2 shows the relative changes of the household emissions under the impacts of the projected urbanisation. In the baseline scenario, the urbanisation will decrease the household emissions by 0.2%–0.4%; in the tax scenarios, the urbanisation will strengthen the negative effect of the tax on the household emissions by 0.3%–0.8%. The economic intuition underlying Fig. 6.2 is that the urbanisation saved the energy consumption in the transport sector, and thus the carbon tax will decrease more emissions, compared to the case without considering the urbanisation impacts. This finding complies with Liu and Liu (2019) who combined the STIRPAT model with spatial Dubin model to argue that the urbanisation impact on the emissions would become negative, and then the negative impact would gradually become weaker in China. Fig. A6.7 in Appendix A shows that the urbanisation impact on the total emissions is very similar to that on the household emissions.

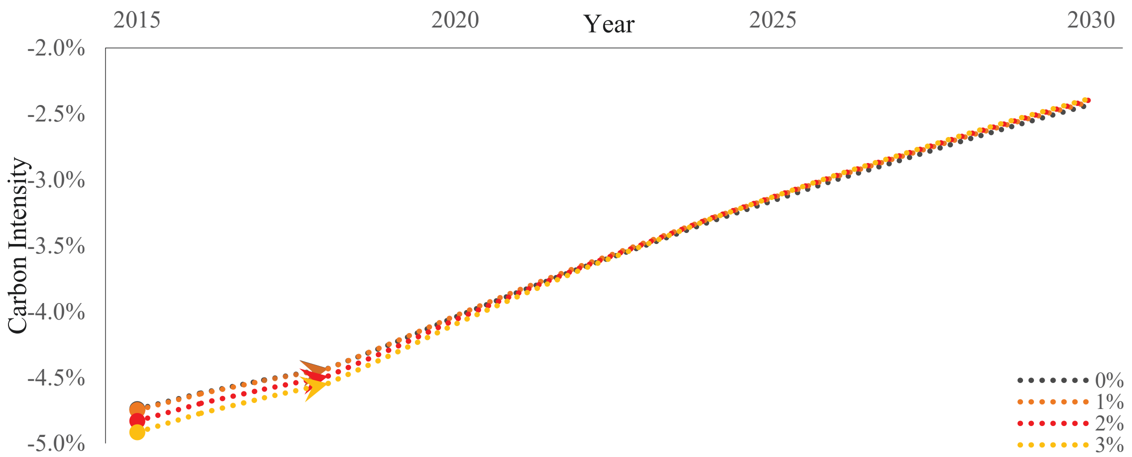


Fig. 6.3 The Urbanisation Impact on the Carbon Intensity

Fig. 6.3 shows the urbanisation impact on the carbon intensity over the studied period. Generally, the urbanisation will decrease the carbon intensity by 2%–5% in the baseline and tax scenarios, and this impact will decline over time. This finding complies with Yao, Kou et al. (2018) who used the threshold regression model to investigate the urbanisation impacts on the emissions in China, empirically showing that the urbanisation contributed to the declines in the carbon intensity, but this abatement effect diminished with the deepening Chinese urbanisation. Similarly, Lin and Zhu (2017) constructed a 4-variable panel vector auto-regression model to study the energy and carbon intensity during the urbanisation, concluding that the energy and carbon intensity would decline with the development of the urbanisation in China.

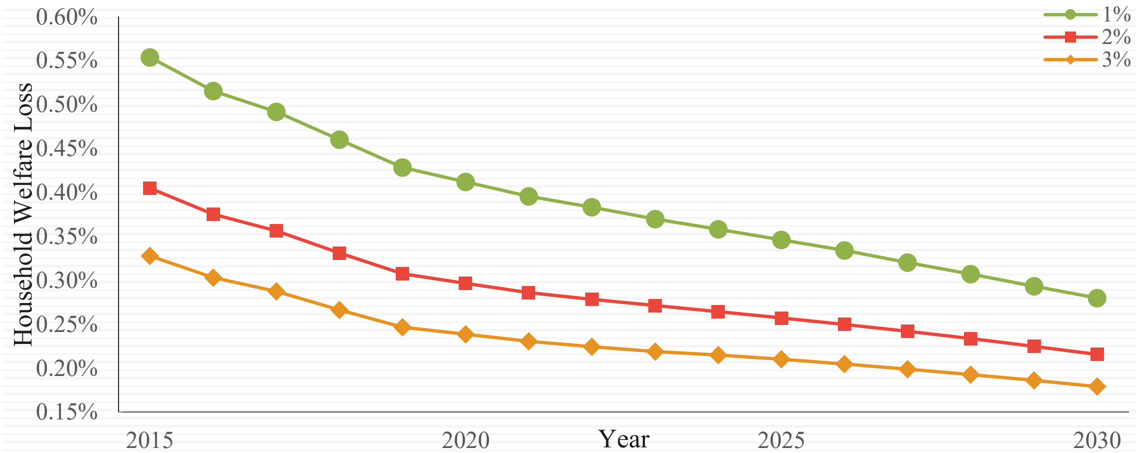


Fig. 6.4 The Urbanisation Impact on the Household Welfare Loss

Fig. 6.4 shows how the urbanisation will affect the household welfare loss, induced by the carbon tax, over the research period. In all the tax scenarios, the urbanisation will increase the welfare loss by 0.15%–0.6%, implying that the urbanisation will reinforce the negative policy effect of the carbon tax on the household welfare. As the time goes by, this urbanisation impact will gradually decrease. The economic intuition underlying Fig. 6.4 is that the household needs the resources to adapt to the lifestyle changes, accompanied by the urbanisation, and thus the household will have fewer resources to cope with the rising energy price under the carbon tax. This finding complies with Miao and Wu (2016) who used the survey data to examine the confounding health impacts of the rapid urbanisation in China, arguing that the urbanisation would negatively affect the social welfare as living in more urbanised areas increased the risks of acquiring chronic diseases.

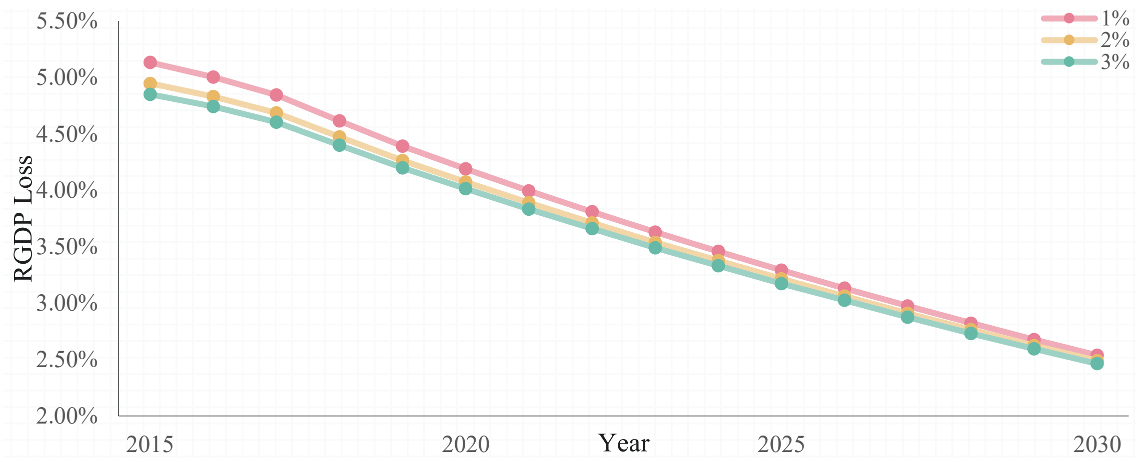


Fig. 6.5 The Urbanisation Impact on the RGDP Loss

Fig. 6.5 shows the urbanisation impact on the RGDP loss, induced by the carbon tax, over the studied period. In the tax scenarios, the urbanisation will increase the RGDP loss by 2.5%–5.5%, implying that it will decrease the RGDP. This urbanisation impact will steadily decline over time, and it is negatively related to the tax rate. Interestingly, the ARDL model shows that the urbanisation will increase the RGDP in the baseline scenario with no tax imposed; the urbanisation will decrease the RGDP in the tax scenarios. The rationale of Fig. 6.5 is that the carbon tax may negatively affect the industrial cluster, induced by the urbanisation, because the tax imposes limitations on the intensive use of energy.

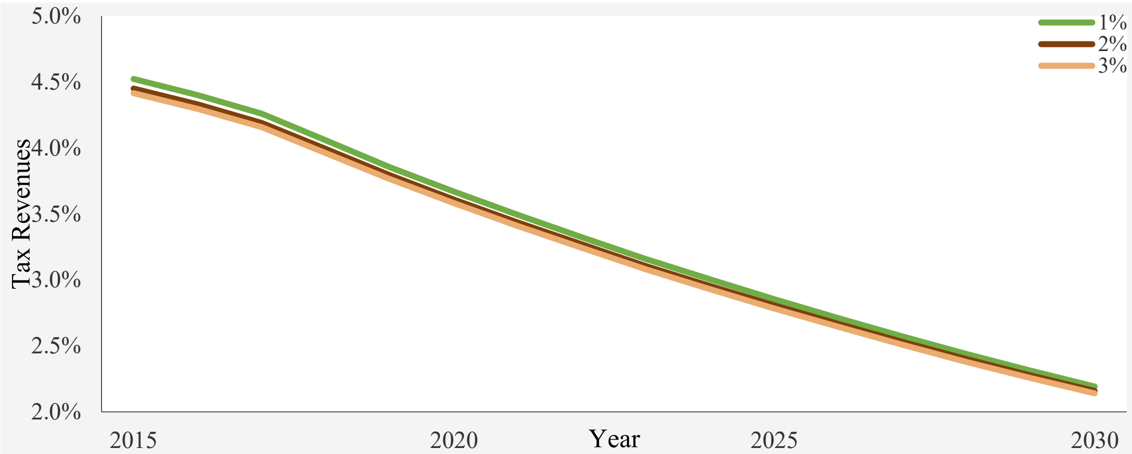


Fig. 6.6 The Urbanisation Impact on the Tax Revenues

Fig. 6.6 shows the urbanisation impact on the revenues generated by the carbon tax. According to Fig. 6.6, the urbanisation will positively affect the tax revenues, but this impact will decline over time. As the tax rate increases, this urbanisation impact will decrease, even though the tax rate will minimally affect this impact. The reason why the urbanisation will increase the tax revenues is that the carbon tax will intervene more on the economy, implied by more RGDP loss under the urbanisation impacts shown in Fig. 6.5.

In Appendix A, Fig. A6.8 shows how the tax marginal effect on the household emissions will change under the urbanisation impact. This tax marginal effect will increase at the 1% tax but decrease at the 2% and 3% tax, when the urbanisation impact is considered. In contrast, Fig. A6.9 shows that the urbanisation will generally decrease the tax marginal effect on the total emissions except that it increased the marginal effect in 2015–2018 at the 1% tax.

Fig. A6.10 in Appendix A shows the urbanisation impact on the tax marginal effect on the carbon intensity. The urbanisation will weaken this marginal effect over the studied period at the 1% tax. However, the urbanisation strengthened the effect in 2015–2016 at the 2% tax and 2015–2019 at the 3% tax but will weaken the effect since 2020 at the 2% and 3% tax. Fig. A6.10 implies that the urbanisation will counteract the tax marginal effect on the intensity reduction in the future. This prohibitive urbanisation impact analysed in this chapter complies with Yang, Fan et al. (2014) who evaluated the potential effects of the Chinese carbon tax on the emission abatement, concluding that the inelastic demand for energy under the rapid urbanisation limited the effectiveness of the Chinese carbon tax.

Fig. A6.11 in Appendix A shows how the urbanisation will affect the tax marginal effect on the household welfare loss. At the 1% tax, this urbanisation impact is positive, whilst it is negative at the 3% tax. When the tax rate is 2%, this urbanisation impact was expected to fluctuate before 2022 but will increase the tax marginal effect in 2023–2030. In contrast, Fig. A6.12 in Appendix A shows that the urbanisation will strengthen the tax marginal effect on the RGDP loss over the research period, but this impact will steadily decrease as the time goes by or the tax rate increases.

Fig. A6.13 in Appendix A shows how the urbanisation will affect the tax marginal effect on the tax revenues. In all the tax scenarios, this urbanisation impact is positive, but it will gradually decrease over time. As the tax rate increases, this urbanisation impact will decline.

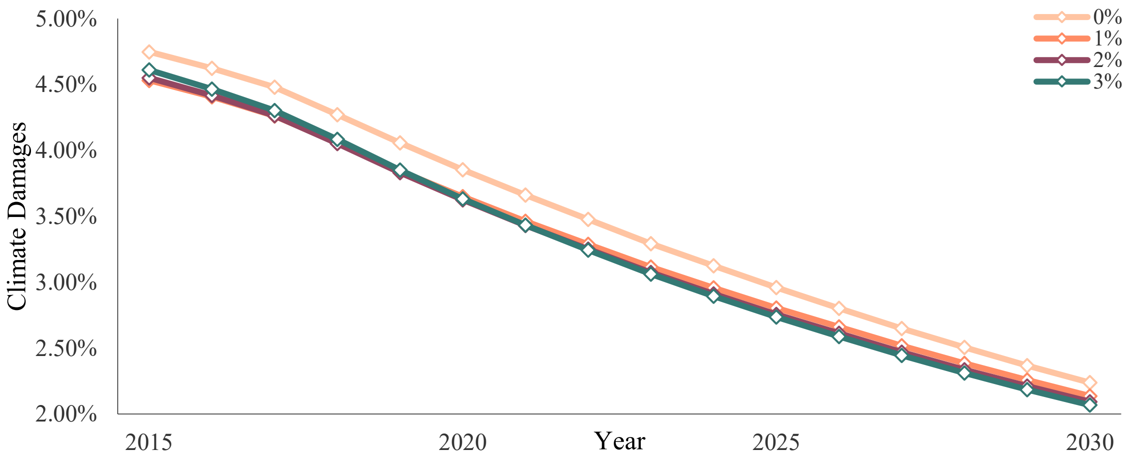


Fig. 6.7 The Urbanisation Impact on the Climate Damages

Fig. 6.7 shows the change of the climate damages in the urbanisation model relative to the inequality model. Generally, the urbanisation will increase the climate damages by 2%–5% in all the scenarios; however, this impact is negatively correlated with the time or tax rate. The rationale underlying Fig. 6.7 is that under the urbanisation impact, the household may be more susceptible to the climate change because of the lifestyle changes induced by the urbanisation. Similar findings could be found in the previous research conducted elsewhere. For example, despite the decline in the annual rainfall, the flood risk increased because of the urbanisation, according to Mahmoud and Gan (2018) who analysed the urbanisation and climate change impact on the flood risk of two governorates in Egypt. Moreover, the urbanisation exacerbated the flood response in Houston, according to Zhang, Villarini et al. (2018) who studied the potential effects of the urbanisation on the hydrometeorology associated with the hurricane.

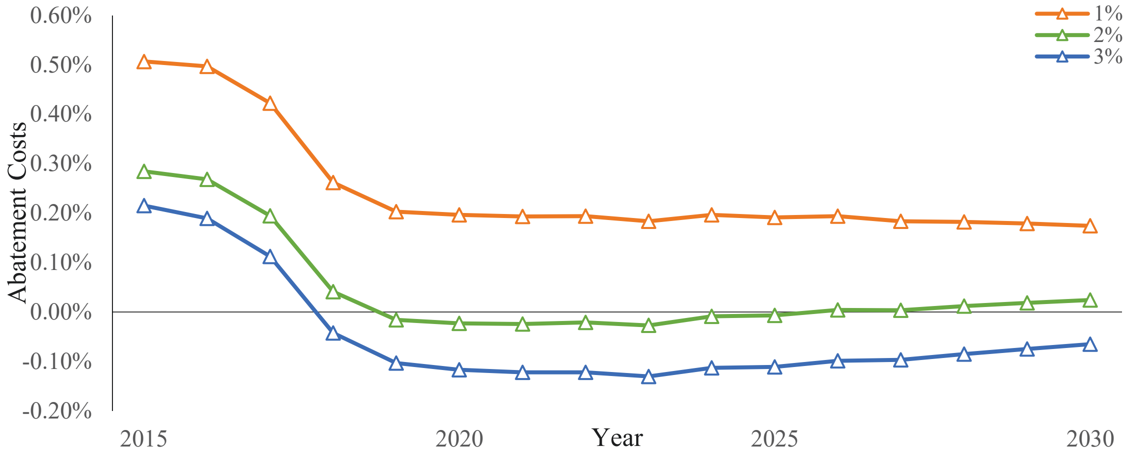


Fig. 6.8 The Urbanisation Impact on the Abatement Costs

Fig. 6.8 shows how the urbanisation will affect the abatement costs in China over the research period. According to Fig. 6.8, the urbanisation will increase the abatement costs at the 1% tax. When the tax rate is 2%, the urbanisation increased the costs in 2015–2019, and then this impact will fluctuate around 0 in the future. At the 3% tax, the urbanisation increased the abatement costs recently but will decrease the costs in 2018–2030. To summarise, as the tax rate increases, the urbanisation impact on the abatement costs will become less or even negative.

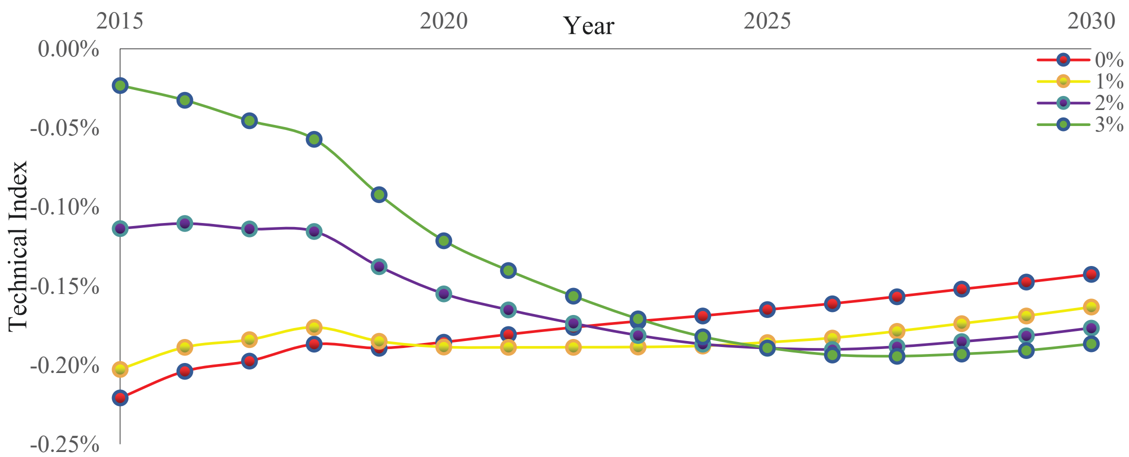


Fig. 6.9 The Urbanisation Impact on the Technical Index

Fig. 6.9 shows the urbanisation impact on the technical index over time. Generally, the urbanisation will decrease the technical index in all the scenarios, and a rise in the tax rate will increase the fluctuation of this urbanisation impact over time. The reason why the urbanisation will discourage the technical innovation is that the carbon tax may impede the sharing of the information and technological spill-over as the industrial cluster, inducing the intensive use of energy, is unfavourable under the tax. This finding agrees with the previous study showing that the urbanisation could have a negative impact on the low-carbon development in the urban area of China, according to Qu and Liu (2017) who established a regional low-carbon development indicator system to evaluate the low-carbon development in China.

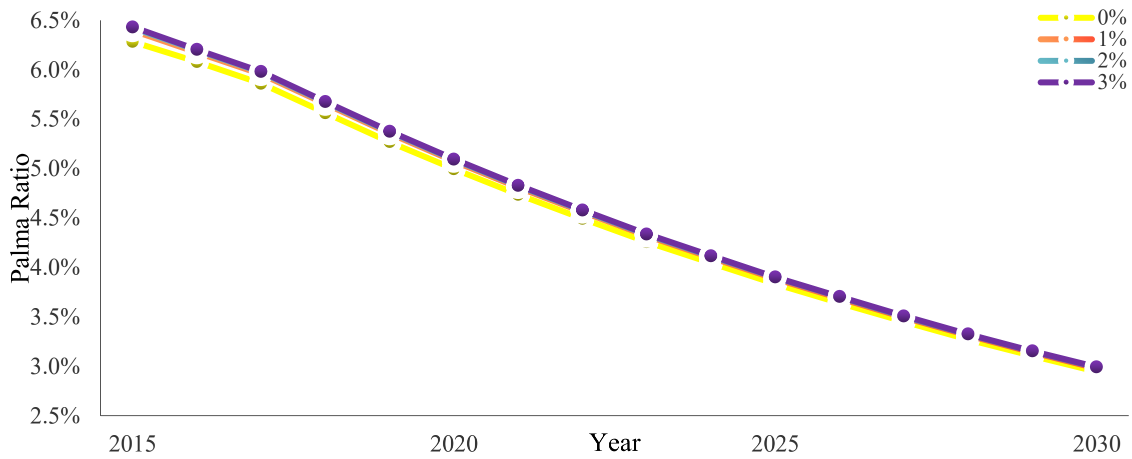


Fig. 6.10 The Urbanisation Impact on the Palma Ratio

Fig. 6.10 shows the changes of the Palma ratio under the urbanisation impact over time. In all the scenarios, the urbanisation will increase the Palma ratio by 3%–6.5%, implying that the urbanisation will increase the social inequality. This urbanisation impact will decrease over time but remain relatively stable as the tax rate increases. The economic intuition underlying Fig. 6.10 is that the adverse impact of the lifestyle changes, induced by the urbanisation, will be more distinct on the low-income household who will have fewer resources to cope with the rising energy price under the carbon tax. This finding complies with Zhang (2016) who examined the trends, promises, and challenges of the world urbanisation, arguing that the city size was positively correlated with the likelihood of the inequalities.

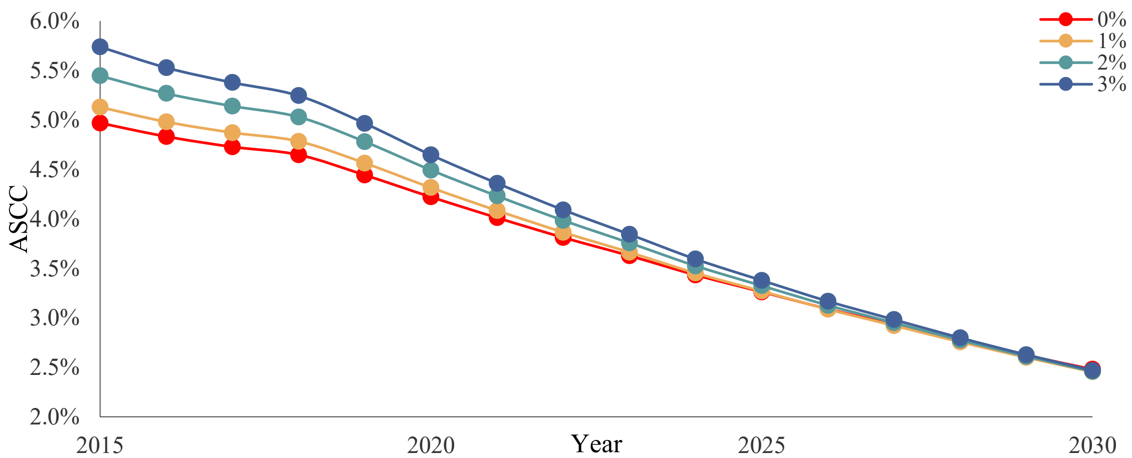


Fig. 6.11 The Urbanisation Impact on the Average Social Cost of Carbon (ASCC)

Fig. 6.11 shows how the ASCC will be affected by the urbanisation. In all the scenarios, the urbanisation will increase the ASCC by 2.5%–6%, but this impact will decline over the research period. A rise in the tax rate will increase this urbanisation impact, but the influence of the tax rate will diminish over time. The rationale of Fig. 6.11 is that the urbanisation will decrease the household welfare (shown in Fig. 6.4) and RGDP (shown in Fig. 6.5) and increase the climate damages (shown in Fig. 6.7) under the carbon tax. This finding agrees with Lee (2019) who adopted the panel data analysis methods to analyse the urbanisation impacts on the carbon footprint in Asia, concluding that the urbanisation could increase the carbon footprint of the entire region and thus increase the ASCC in China.

Table 6.6 The Urbanisation Impact on the Relative Utility and Household Welfare

Tax Rate	0%	1%	2%	3%
Relative Utility	1.52%	1.63%	1.62%	1.59%
Household Welfare	0.00%	-0.06%	-0.06%	-0.02%

Table 6.6 shows the differences of the relative utility and household welfare between the urbanisation model and inequality model. As the urbanisation increases the inequality, it will increase the absolute value of the relative utility. By comparison, the urbanisation will have almost no impact on the household welfare in the baseline scenario, but it will slightly decrease the welfare when the carbon tax is imposed. This finding complies with the previous research implying that the unfair distribution of the social welfare, induced by the rapid urbanisation, became a serious problem threatening the social stability in China (Cao, Lv et al. 2014).

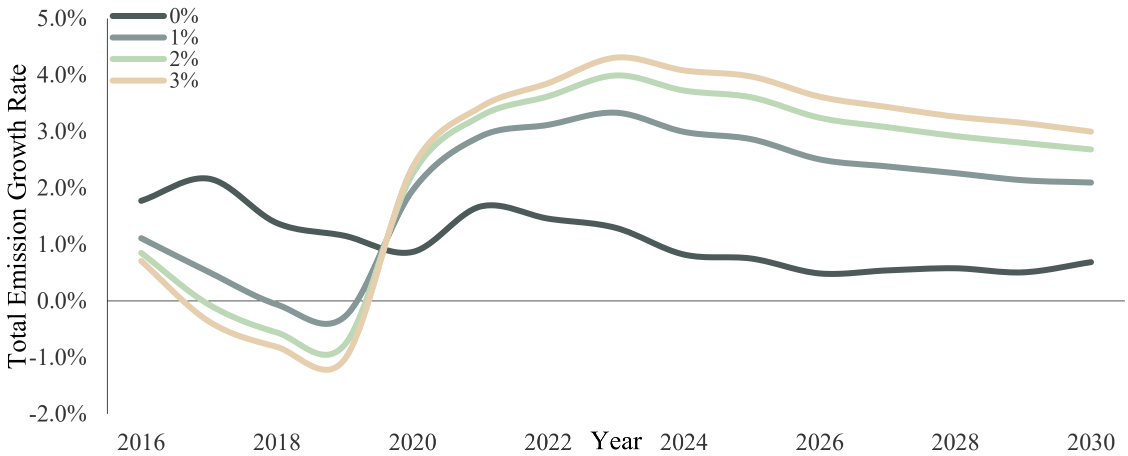


Fig. 6.12 The Urbanisation Impact on the Total Emission Growth Rate

Fig. 6.12 shows the projected emission growth rate over the studied period under the urbanisation impacts. In all the scenarios, the emission growth rate in 2030 will not approach zero. This finding implies that considering the ancillary and primary benefits as well as the technical and urbanisation impacts, the carbon tax will not help China meet the INDC target of peaking its emissions in 2030. As Fig. 6.3 shows that the urbanisation will negatively affect the carbon intensity, China will still meet its INDC target of the carbon intensity reduction in 2030 under the urbanisation impacts.

Discussion

This chapter empirically shows that the urbanisation will decrease the carbon emissions and intensity over the studied period. This finding is contrary to Wang, Wu et al. (2016) who argued that the urbanisation increased the carbon emissions in China. The result difference between Wang, Wu et al. (2016) and this chapter is caused by the choices of the explanatory variables: Wang, Wu et al. (2016) omitted the correlation between the urbanisation and GDP, whilst this chapter has fully explored the interrelations among the GDP, emissions, energy consumption, and urbanisation. Considering that China has recently developed the green, circular, and low-carbon economy (He 2016), the omission of the economic factor is likely to result in a biased evaluation of the urbanisation impact on the emissions.

In the baseline scenario, the urbanisation will promote the GDP growth. This finding agrees with Yang, Liu et al. (2017) who used the STIRPAT model to investigate the urbanisation impacts based on the data of the 266 prefecture-level Chinese cities in 2000–2010, concluding that the urbanisation impact on the economic growth was positive and significant. However, in the tax scenarios, the urbanisation will negatively affect the economic growth in the studied period. This finding corresponds to Liddle (2013) who adopted a panel method to show that the urbanisation had a “ladder” impact on the income: it had a strong negative impact on the poorest countries, a less negative to neutral impact on the countries with the moderate incomes, and a reinforcing impact on the wealthy countries. As the carbon tax will decrease the national income according to the previous chapters, the urbanisation impact on the economic growth could become negative if the tax is imposed.

Although the urbanisation may stimulate the economic growth depending on the imposition of the carbon tax, it will reduce the household welfare over time. This finding corresponds to the argument that the urbanisation might lead to the unhealth lifestyles: the populations experiencing the urbanisation would consume more fat and smoke more frequently, implied by the community and individual-level longitudinal data from the China Health and Nutrition Survey, according to Van de Poel, O'Donnell et al. (2012). By comparison, Chen, Liu et al. (2017) investigated the impacts of the Chinese urbanisation on individual health, showing that there existed an inverted U-shaped relationship between the health and urbanisation (with a turning point of the urbanisation rate at 42.0%). As Table 6.1 shows the projected urbanisation in the studied period 2015–2030 will exceed 42.0%, hence, the urbanisation will negatively affect the household welfare.

The urbanisation will increase the tax revenues over the research period. In the literature, very little research has been conducted to analyse the urbanisation impacts on the revenues of climate policies. However, the primitive goal of the Chinese urbanisation is to generate governmental revenues, according to Ye and Wu (2014) who used the panel data of the 286 Chinese prefecture-level cities in 1999–2009. Hence, the argument in Ye and Wu (2014) verifies the positive impacts of the urbanisation on the tax revenues in this chapter.

The urbanisation impact on the abatement costs is complicated: a lower tax may increase the abatement costs, whilst a higher tax may decrease the costs. The positive impact complies with Bretschger and Zhang (2017) who developed a general equilibrium model to estimate the cost of the climate policy, concluding that the urbanisation increased the policy cost because the urban households consumed more energy and energy-intensive goods in China. In contrast, the negative impact agrees with Xi, Fei et al. (2013) who adopted a simplified method built upon benefit transfer to present a case study of co-benefits in the cement sector, indicating that the Chinese urbanisation brought about significant co-urban benefits, including the substantial reduction of the marginal abatement costs.

The urbanisation will pose an adverse impact on the technical progress. This finding is contrary to Duman and Kasman (2017) who empirically showed that the urbanisation improved the environmental technical efficiency in the European Union. The result difference between Duman and Kasman (2017) and this chapter lies in the targeted scope of the induced technological change: Duman and Kasman (2017) only researched the environmentally friendly technologies, whilst the technical index in this chapter is a general index that considers all kinds of technologies. In the reality, the urbanisation may lay influences on the development of the technologies that are not environmentally friendly. According to Shahbaz, Chaudhary et al. (2017) who employed the STIRPAT model to investigate the relationship between the urbanisation and energy consumption, there was a bidirectional causality between the technology and energy consumption under the urbanisation impacts in Pakistan.

The embedded assumption of exogenously introducing the urbanisation impacts in this chapter is different from endogenously determining the ancillary and primary benefits and technical impacts in the previous chapters. This embedded assumption is due to the division of the population data: the representative household of the CGE model has been divided into three income subgroups in the previous chapter, and it is not easy to find the data of the rural and urban population dispersion within the income subgroups. Hence, in this chapter, the urbanisation is assumed to exogenously affect the model equilibrium rather than endogenously change the urban-rural population ratio in the income subgroups to determine the optimal climate policy.

In summary, the urbanisation will decrease the emissions and intensity, induce more household welfare loss under the carbon tax, increase the climate damages and abatement costs, discourage the technical innovation, and deteriorate the social inequality. Noticeably, all these mentioned urbanisation impacts are quite minimal, which verifies that introducing the urbanisation as an exogenous variable is meaningful. The exogenously determined urbanisation impacts may not fully explore the mechanism that the urbanisation influences the policy effects of the carbon tax. This is because the optimal policy is based on the given inputted parameters describing the urbanisation impacts, but these parameters should vary freely to form the optimal policy. Hence, future research may lie in the use of detailed urban-rural population dispersion data to endogenously model the urbanisation as an influential factor of the carbon tax.

The Tinbergen Rule argues that an efficient policy requires at least as many independent policy instruments as there are policy targets (Schader, Lampkin et al. 2014). I have already considered many influential factors of the carbon tax in the previous chapters, and these factors may correlate with the urbanisation impacts analysed in this chapter. Hence, the simulated carbon tax may not reveal the genuine urbanisation impacts.

Policy Implications

The urbanisation will strengthen the policy effects of the carbon tax on the emission reduction as well as the household welfare loss and real GDP loss. In the tax scenarios, the urbanisation will increase the climate damages, discourage the technical innovation, deteriorate the inequality condition, and increase the average social cost of carbon (ASCC).

Conclusion

The urbanisation had a negative impact on the carbon emissions but positive impact on the GDP in 1980–2014, and these impacts were both statistically significant. However, the urbanisation impact on the energy consumption was not statistically significant. The urbanisation will decrease the household emissions by 0.2%–0.8% and carbon intensity by 2%–5% in 2015–2030. Although the urbanisation will increase the real GDP (RGDP) in the baseline scenario, it will decrease the RGDP in the tax scenarios. Similarly, it will increase the household welfare loss of the carbon tax by 0.15%–0.6%, depending on the tax rate and time. The urbanisation will decrease the tax marginal effects on the total carbon emissions, whilst the marginal effects on the RGDP loss and tax revenues will be reinforced under the urbanisation impacts.

The urbanisation will increase the climate damages by 2%–5%, but this impact will decline over time. By comparison, at the 1% tax, the urbanisation will increase the abatement costs, but at the 3% tax, the urbanisation increased the costs in 2015–2019 but will decrease the costs in 2020–2030. The urbanisation will decrease the technical index by less than 0.25%, implying that it will slightly discourage the technical innovation. The urbanisation will increase the Palma ratio by 3%–6.5%, implying that it will increase the inequality condition. The urbanisation will increase the average social cost of carbon (ASCC) by 2.5%–6%. Considering the urbanisation impacts, the carbon tax still cannot help China meet the INDC target of peaking the emissions in 2030.

Chapter 7: Comparing the Emission Trading Scheme with the Carbon Tax

Introduction

An emission trading scheme (ETS) or cap and trade is another very popular climate policy intended for curbing carbon emissions. In an ETS, the participating entities are allocated a certain quantity of carbon quotas within a specified period. The entities have options to either consume or trade the quotas, depending on the marginal costs: if the marginal costs are higher than the carbon price, entities will buy additional quotas from the market; if the costs are lower, entities will sell their superfluous quotas (Dai, Xie et al. 2018). In a word, owners of the rights to pollute the atmosphere would charge for allowing individuals and organisations to emit CO_2 (Allan, Lecca et al. 2014).

The socioeconomic impacts of an ETS policy have been previously studied in a variety of contexts. For example, Choi, Liu et al. (2017) employed a CGE model and empirically found that the South Korean ETS had significant abatement effects with mild negative impacts on the GDP and household consumption. Loisel (2009) adopted a comparative approach via a dynamic CGE model, empirically showing that the ETS implementation encouraged the economic growth in Romania. Nong, Meng et al. (2017) employed the MONASH-Green model, concluding that the operation of the proposed ETS in Australia would cause the economy to contract progressively over the lifetime of the ETS. Overall, the previous evidence suggests that an ETS policy can help meet a climate mitigation target, but it poses a negative impact on GDP. However, an ETS policy may result in a more attractive economic outcome compared to a carbon tax, because a carbon tax may have a punishing impact on productive activities and economic growth (Loisel 2009).

A carbon tax usually requires strong governmental administrative power, while an ETS policy requires a solid carbon market to be established (Liu and Lu 2015). As China has a strong government and its nationwide carbon market is quite rough with low efficiencies (Lin and Jia 2019), a carbon tax seems to be preferable. However, Dai, Xie et al. (2018) used a CGE model to evaluate the economic impacts of the Chinese INDC, empirically confirming the economic efficiency of the simulated ETS policy since the emission reduction targets could be achieved at lower costs. The ETS implementation in one of the seven pilots (Hubei) showed a noticeable emission reduction with negligibly adverse impacts on the provincial GDP and household consumption, according to Liu, Tan et al. (2017) who applied a Chinese multi-regional general equilibrium model.

In addition to the designed nationwide ETS in China only, some researchers simulated a conceivable multi-region integrated ETS where China participated (Hubler, Voigt et al. 2014, Zhang, Qi et al. 2017). A multi-region ETS could accelerate the reduction of coal consumption and facilitate the development of clean energy in China (Zhang, Qi et al. 2017). For example, linking the Chinese

ETS and European Union (EU) ETS slightly attenuated the welfare and GDP loss, compared to the single-region ETS in China, according to Hubler, Voigt et al. (2014) who employed a multi-region and multi-sector CGE model to study the policy effects of the Chinese ETS policy.

The ETS market around the world is sophisticated. For example, South Korea implemented a national ETS covering the main industrial and power sectors, and the Korean ETS is the second largest carbon market in the world (Suk, Lee et al. 2018). The EU ETS is now the largest ETS in the world (Crossland, Li et al. 2013). According to International Carbon Action Partnership (ICAP 2020), the scope of covered industries in the EU ETS has been evolving: in Phase I (2005–2007), the covered industries mainly consisted of the electricity, energy production, and nonmetal production industry; in Phase II (2008–2012), the aviation industry was added; in Phase III (2013–2020), the metal production and chemistry industry were included, implying that almost all the industries are now covered by the EU ETS (Lin and Jia 2017, Lin and Jia 2020, Lin and Jia 2020); in Phase IV (2021–2030), the scope of covered industries will not change in the EU ETS. Despite its wide industrial coverage in Phase III and IV, the EU ETS regulates only 45% of the EU greenhouse gas emissions at present (Verde, Teixido et al. 2019, ICAP 2020), implying that the EU anthropogenic emissions are also regulated by other climate policies, like carbon taxes.

Compared to the other sophisticated ETS markets in the world, the Chinese ETS market has been constructed very recently. China launched the pilot ETS market in seven municipalities and provinces in 2013, but each pilot had only a few but different ETS-covered sectors (Zhang, Xu et al. 2019). After several years of the trial, the period 2017–2020 was the phase for launching and initial operations of a national ETS (Liu and Fan 2018); however, the pilot ETS policy lacked the details of sectoral coverage (Lin and Jia 2019).

As the Chinese ETS market is relatively new, uncertainty remains about the appropriate sectoral coverage. Lin and Jia (2020) designed an ETS policy with various sectoral coverages from the electricity sector only to all the sectors, and they used a dynamic recursive CGE mode to conclude that a higher sectoral coverage would lead to the higher GDP and lower ETS price. However, the overall emission reduction or carbon intensity reduction was not linearly correlated with the coverage rate (Lin and Jia 2020). Instead, there was a U-shaped relationship between the coverage and energy efficiency or between the coverage and actual emissions (Lin and Jia 2020). The emission costs in the full coverage scenario were higher than the other scenarios (Lin and Jia 2020). Nevertheless, it is very hard to find the lowest point of the two U-shaped curves. In the realty, according to the official document published by National Development and Reform Commission (NDRC) in 2017, only the power generation industry would be covered in the Chinese ETS market (Lin and Jia 2020). The current industrial coverage in the Chinese ETS market is even lower than the EU ETS in Phase I. Hence, the sectoral coverage of the Chinese ETS policy needs expanding, otherwise it would not be a nationwide policy.

Moreover, there is no compound index put forward in Lin and Jia (2020) to comprehensively evaluate the socioeconomic and environmental impacts of the industrial coverage rate in the ETS market.

By comparison, Chen, Shi et al. (2020) adopted the difference in differences (DID) method to investigate the nationwide impacts of the ETS policy in the Chinese pilots only. They empirically found the Chinese pilot ETS reduced the nationwide carbon emissions by 13.39% on average with a growing trend, increasing from 11.23% to 16.95% in 2013–2016. If a nationwide ETS policy had been implemented, China would have achieved a much larger emission reduction in the past. Hence, in this chapter, I have studied the policy effects of the nationwide ETS policy covering all the sectors except the electricity subsectors exploiting renewables only. This is because the subsectors exploiting renewables have very few emissions, and thus they should not be regulated by climate policies in abating emissions. Instead, they should be supported to develop owing to the importance of renewable energy to sustainable development, diversification of energy supply, and preservation of the environment (Sims 2004). However, such supports are not considered in this chapter, because the supports are beyond the domain of the ETS policy.

The quantification of the ETS policy in this chapter is mainly based on Lin and Jia (2018). Generally, their research attempted to capture the ETS policy effects on the Chinese social welfare as well as the completion of the INDC targets. However, the ETS market in their research did not allow the sectors, whose emissions were less than the carbon quotas, to sell the surplus quotas to those who had excess emissions. This chapter relaxes this assumption by allowing the surplus carbon quotas to be traded under the ETS policy. Moreover, the industrial classification in Lin and Jia (2020) was quite broad: the electricity sector faced the same carbon price in the ETS market, implying that the electricity subsectors exploiting renewables only were also regulated by the ETS policy. By comparison, in this chapter, the detailed disaggregation of the electricity sector separates the electricity subsectors exploiting renewables only, and these subsectors are not covered by the ETS policy. Like Lin and Jia (2017), the carbon market, in this chapter, is assumed to be perfect competitive, where the carbon price equals the equilibrium trading price if the carbon quotas are tradeable or the carbon price is endogenously determined if the quotas are untradeable.

In the literature, most researchers evaluated an ETS policy using the cost-benefit analysis in comparison with a carbon tax. The cost-benefit analysis may not directly and conspicuously answer which climate policy is preferable, because an ETS or carbon tax could have very different emission and welfare effects. For example, Li and Jia (2017) used a dynamic recursive CGE model and empirically found that the carbon tax would reduce the emissions by 10%–13% and incur the unit emission cost at 98–241 $\$/t\ CO_2$ depending on the tax rate, whilst the ETS policy could reduce the emissions by 12%–13% and incur the unit cost at 64–76 $\$/t\ CO_2$ depending on the trading price. Readers may draw a misleading conclusion that the ETS was preferable because it reduced more emissions and incurred the lower unit emission cost. However, this conclusion is variant to the scenario settings of the low, middle, and high tax rate and carbon price. In the literature, there was no consensus on the corresponding tax rate and carbon price comparison between the two policies (Yoon and Jeong 2016, Dissanayake, Mahadevan et al. 2020). More importantly, the amount of the emission reduction may not be linearly correlated with the abatement costs, according to Lu and Stern (2016) who employed an intertemporal CGE model to study the relationship between the substitutability and cost of climate policy. Higher emission reduction could induce higher unit abatement cost (Liu, Sun et al. 2016). Hence, the comparisons of the different emission and welfare effects make no sense.

This chapter contributes to the literature by developing a direct unbiased comparison of the policy effects between the carbon tax and ETS policy. The direct comparison can be either the emission reduction effects at the same welfare change or the welfare effects at the same targeted emission reduction. Most international agreements on the climate change have clear emission reduction targets, but very few agreements include welfare targets. Hence, in this chapter, the ETS policy is designed with the same emission effects as the carbon tax simulated in the previous chapters, but the ETS policy may have very different welfare effects. In other words, the abatement target of the designed ETS policy is based on the tax rate of the carbon tax. For example, if a 1.5% carbon tax decreases the carbon emissions by 10%, then 10% becomes the targeted emission reduction of the ETS policy. At this point, the comparison of the welfare effects will unbiasedly reveal which climate policy is preferable.

Method

The carbon-cap policy is built as the solid foundation of the ETS policy, where the carbon market is assumed to be perfect competitive. Under the carbon-cap policy, the carbon quotas are allocated basing on the historical emissions. In other words, the quota allocation is based on the grandfather method (Verde, Teixido et al. 2019). According to Wu and Zhang (2019), there are three fundamental schemes to allocate the quotas, basing on historical emissions, GDP, and population respectively. Although the quota allocation scheme basing on historical emissions will result in more welfare for regions with more carbon emissions (Wu and Zhang 2019), this allocation scheme will result in the largest welfare for the society among the three schemes (Wu and Zhang 2019). Hence, in this chapter, the quota allocation is based on the carbon emissions in 2015 or 2005, which is named as the 2015 and 2005 scheme respectively shown in Eq. (7.1).

$$CR_{es,t} = E^0_{es,2015} \; or \; E^0_{es,2005} \tag{7.1}$$

In Eq. (7.1), $CR_{es,t}$ stands for the allocated carbon quotas in Sector es in Year t, and it is time-invariant; $E^0_{es,2015}$ and $E^0_{es,2005}$ denote the baseline emissions of Sector es in 2015 and 2005 respectively. Eq. (7.1) shows the sectoral carbon quotas are set to equal the corresponding sectoral emissions in 2015 or 2005. The reason why the ETS is based on the 2015 emissions is that 2015 is the beginning year of the studied period 2015–2030. By comparison, basing the 2005 emissions corresponds to the fact that China has pledged to lower its carbon emissions per unit of GDP by 60% to 65% from the 2005 level by 2030 in its Intended Nationally Determined Contributions (INDC) in 2015 (NDRC 2015).

Regarding the allocation method, there are generally two options, namely free allocation and auction (Wu, Fan et al. 2016). Auction could be more efficient than free allocation when it was appropriately planned, according to Betz, Seifert et al. (2010) who designed the Australian carbon pollution reduction scheme. As China started to construct its nationwide ETS market in 2017, and more than 90% of the carbon quotas were free in the pilot carbon markets (Wu and Li 2020). Hence, the free allocation is the main method to distribute the carbon quotas at the current stage in China (Liu, Sun et al. 2016, Li, Zhang et al. 2018). According to Wang, Zhou et al. (2019) who verified the effectiveness of the carbon quota policy by examining a supply chain, carbon quota policies around the world are very similar: a phase of completely free allocation followed by a phase of decreasing quotas year by year. Hence, in this chapter, the free allocation is the adopted method to distribute the carbon quotas among the sectors; however, the free allocation will decline over time shown in Eq. (7.2).

$$FCQ_{es} = CR_{es} \times far \times (1 - \omega) \tag{7.2}$$

In Eq. (7.2), FCQ_{es} denotes the free allocation of the carbon quotas in the sector es; far refers to the rate of the free quotas, and its value equals 0.9 in the period according to the seven pilot cities in China as well as the period I in EU-ETS (Lin and Jia 2018). The free allocation rate is assumed to be equal across the ETS-targeted sectors. ω refers to the annual decline factor of the free allocation, and its potential value is 0%, 0.5%, 1% and 2% in Guangdong Province, an ETS pilot in China (Lin and Jia 2018). Eq. (7.2) shows that the free quotas in the base year (2015) are assumed to equal the carbon quotas multiplied by the free allocation rate and deducted by the decline factor. To study the socioeconomic impacts of the ETS carbon pricing, Lin and Jia (2019) assumed that the free quotas could not be traded or transferred, whilst the paid parts of the carbon quotas could be traded in the ETS market. In contrast, the free quotas could be traded under the ETS policy in this chapter.

$$CEcost_{es,t} = \begin{cases} P_t^{ets} \times (CR_{es} - FA_{es}) + P_t^{fine} \times \left(E_{es,t}^{ets} - CR_{es}\right), E_{es,t}^{ets} \geq CR_{es} \\ P_t^{ets} \times (CR_{es} - FCQ_{es}), E_{es,t}^{ets} < CR_{es} \end{cases} \tag{7.3}$$

$$P_t^{fine} = 2 \times P_t^{ets} \tag{7.4}$$

According to Lin and Jia (2018), the emission costs under the carbon-cap or ETS policy are defined in Eq. (7.3). The subscript es denotes the industries covered by the carbon-cap or ETS policy. $CEcost_{es,t}$ is the emission costs in Sector es in Year t. P_t^{ets} is the normal carbon emission price in Year t. P_t^{fine} is the fine price of the over-emissions in Year t, which is much higher than P_t^{ets}. According to Lin and Jia (2018), the fine price of the over-emissions is twice the normal carbon price shown in Eq. (7.4). $E_{es,t}^{ets}$ refers to the carbon emissions of Sector es in Year t under the carbon-cap or ETS policy.

$$\begin{cases} SGDP_{es,t}^{ets} = SGDP_{es,t}^{0} - CEcost_{es,t} \\ SGDP_{nes,t}^{ets} = SGDP_{nes,t}^{0} \end{cases} \tag{7.5}$$

$$SFuel_{iqt}^{ets} = SFuel_{iqt}^{0} \times \frac{SGDP_{it}^{ets}}{SGDP_{it}^{0}} \tag{7.6}$$

$$E_{it}^{ets} = \sum_q (SFuel_{iq}^{ets} \times CEF_q) \tag{7.7}$$

In Eq. (7.5), $SGDP_{es,t}^{ets}$ refers to the sectoral output under the carbon-cap policy. Eq. (7.5) shows that the sectoral output under the carbon-cap policy equals the baseline sectoral output minus the sectoral carbon emissions cost. By comparison, for the industries that are not covered by the carbon-cap policy, their sectoral output is always equal to the baseline sectoral output. Eq. (7.6) shows that the sectoral energy use under the carbon-cap policy is proportional to the sectoral output change relative to the baseline sectoral output if the sectoral energy intensity remains unchanged. $SFuel_{iqt}^{ets}$ and $SFuel_{iqt}^{0}$ refer to the sectoral energy use under the carbon-cap policy and baseline scenario respectively; the subscript q refers to a type of energy. Eq. (7.7) shows that the sectoral emissions under the carbon-cap policy equal the summation of the consumed energy multiplied by the corresponding carbon emission factors. CEF_q refers to the carbon emission factor of Energy q.

$$\sum_i E_{it}^{ets} = \sum_i \sum_q (SFuel_{iqt}^{ets} \times CEF_q) = \sum_i E_{it} \tag{7.8}$$

In this chapter, the equilibrium condition is that the overall sectoral emissions under the carbon-cap policy equal that under the carbon tax, shown in Eq. (7.8). Under this condition, the welfare effects could reveal which climate policy is preferable. The welfare effects are denoted by the real GDP (RGDP) and household welfare. The RGDP under the carbon-cap policy is defined in Eq. (7.9), where $RGDP_t^{ets}$ refers to the real GDP in Year t under the carbon-cap policy. The RGDP in Eq. (7.9) is modified by the technical index.

$$RGDP_t^{ets} = \sum_i SGDP_{it}^{ets} \times \frac{ATC_t}{ATC_0} \tag{7.9}$$

$$HD_{it}^{ets} = HD_{it}^{0} \times \frac{SGDP_{it}^{ets}}{SGDP_{it}^{0}} \tag{7.10}$$

$$EV_t^{ets} = \sum_i \left(PQ_{it}^{0} \times HD_{it}^{ets}\right) - \sum_i \left(PQ_{it}^{0} \times HD_{it}^{0}\right) \tag{7.11}$$

Eq. (7.10) defines the household consumption on the assumption that the household consumption changes proportionally to the sectoral output. HD_{it}^{ets} refers to the household consumption of Commodity i in Year t under the carbon-cap policy. Eq. (7.11) shows that the household welfare change is denoted by the equivalent variation (EV) where EV_t^{ets} shows the EV in Year t under the carbon-cap policy.

$$HDFuel^{ets} = HDFuel^{0} \times \frac{HD^{ets}}{HD^{0}} \tag{7.12}$$

Eq. (7.12) shows the household energy consumption under the carbon-cap policy is assumed to change proportionally to the household consumption of commodities relative to the baseline scenario. $HDFuel^{ets}$ and $HDFuel^{0}$ refers to the household energy consumption under the carbon-cap policy and baseline scenario respectively. Noticeably, the subscript of the variables in Eq. (7.12) is omitted because of the unit inconformity, which is explained by the corresponding relations between energy and commodity consumption shown in Table A7.1 in Appendix A.

According to Table A7.1, there is no relation between energy and commodity in crude oil, fuel oil and solar electricity. This is because the household has no energy consumption on these energies. Noticeably, the household has no commodity consumption from the coking industry, but it does have the charcoal consumption. In this chapter, the consumed charcoal is assumed to be related to the commodity from the coal mining and washing industry. The household consumption of liquid energy is assumed to be related to the commodity from the petroleum processing industry, whilst the consumed natural gas is assumed to be related to the summation of the commodities from the gas mining and production industry.

$$HCE_t^{ets} = \sum_q (HDFuel_{qt}^{ets} \times CEF_q) \tag{7.13}$$

Eq. (7.13) shows that the household emissions equal the summation of the consumed energy multiplied by its corresponding carbon emission factor. HCE_t^{ets} refers to household emissions in Year t under the carbon-cap policy.

Under the carbon-cap policy, the sectoral carbon quotas are not allowed to be transacted in the carbon market. However, the surplus carbon quotas can be traded in the carbon market under the ETS policy. The impact comparison of the carbon-cap and ETS policy will reveal the socioeconomic impacts of trading the surplus quotas. In this chapter, the transaction costs of carbon trading are assumed to be zero. Like the carbon-cap policy, the carbon market is assumed to be perfect competitive, and all the above equations also apply under the ETS policy except for the emission costs, shown in Eq. (7.14) and (7.17). The surplus sectoral quotas are assumed to be tradeable, including the free allocation part. If the aggregated sectoral emissions are less than the aggregated carbon quotas, all the sectors can have emissions absorbed by the carbon market through the transaction of the quotas. In other words, no sectors are subject to the fine price of over-emissions. Hence, the emission costs defined in Eq. (7.3) are redefined in Eq. (7.14).

$$CEcost_{es,t} = P_t^{ets} \times (CR_{es} - FCQ_{es}) \tag{7.14}$$

However, in most cases, the aggregated sectoral emissions are larger than the aggregated quotas. At this time, the ETS market cannot fully absorb all the over-emissions, and thus the fine price is applied to the sectors with the over-emissions. The emission costs of the sectors who sell the surplus quotas are still defined in Eq. (7.14). By comparison, the emission costs of the sectors with the over-emissions are defined in Eq. (7.15) to (7.17).

$$Difem_t = \sum_{es} E^{ets}_{es,t} - \sum_{es} CR_{es} \tag{7.15}$$

$$SDifem_{oes,t} = Difem_t \times \frac{E^{ets}_{oes,t}}{\sum_{es} E^{ets}_{oes,t}} \tag{7.16}$$

$$CEcost_{oes,t} = P^{ets}_t \times \left(E^{ets}_{oes,t} - SDifem_{oe,t}\right) + P^{fine}_t \times SDifem_{oes,t} \tag{7.17}$$

Eq. (7.15) defines the over-emissions that cannot be covered by the ETS market, and $Difem_t$ refers to the over-emissions. Eq. (7.16) defines the sectoral over-emissions where the subscript oes refers to the sectors with the over-emissions, and $SDifem_{oes,t}$ refers to the sectoral over-emissions. The embedded assumption in Eq. (7.16) is that the over-emissions are distributed proportionally to the sectoral emissions. Eq. (7.17) defines the emission costs of the sectors with the over-emissions.

According to Deng, Li et al. (2018) who used the propensity score matching–difference in differences (PSM-DID) model to comprehensively analyse the pilot ETS policy, most sectors with free quotas chose to bank all their surplus quotas in the Chinese pilots. The reluctance to sell surplus quotas is equivalent to the situation where free allocation is untradeable. Under the untradeable free allocation, the emission costs of the sectors with the surplus quotas are still defined in Eq. (7.14). The tradeable part of the surplus quotas is defined in Eq. (7.18). To determine whether the surplus quotas excluding the free quotas can cover the over-emissions, Eq. (7.15) is redefined in Eq. (7.19). In Eq. (7.18) and (7.19), the subscript ses refers to the sectors with the surplus quotas; $TCR_{ses,t}$ refers to the tradeable quotas of Sector ses in Year t. Following the determination of $Difem_t$, the emission costs of the sectors with the over-emissions are calculated using Eq. (7.16) and (7.17).

$$TCR_{ses,t} = \begin{cases} CR_{ses} - FCQ_{ses}, FCQ_{ses} \geq E^{ets}_{ses,t} \\ CR_{ses} - E^{ets}_{ses,t}, FCQ_{ses} < E^{ets}_{ses,t} < CR_{ses} \end{cases} \tag{7.18}$$

$$Difem_t = \sum_{oes}(E^{ets}_{oes,t} - CR_{oes}) - \sum_{ses} TCR_{ses,t} \tag{7.19}$$

To compare the welfare effects of the ETS policy relative to the carbon tax, the absolute and relative change of the RGDP and household welfare, denoted by the equivalent variation (EV), are defined in Eq. (7.20) and (7.21), where $\Delta RGDP^{ets}_t$ and $\Delta RG\dot{D}P^{ets}_t$ refer to the absolute and relative change of the RGDP respectively; ΔEV^{ets}_t and $\Delta E\dot{V}^{ets}_t$ refer to the absolute and relative change of the EV respectively.

$$\begin{cases} \Delta RGDP^{ets}_t = RGDP^{ets}_t - RGDP_t \\ \Delta RG\dot{D}P^{ets}_t = \Delta RGDP^{ets}_t / RGDP_t \end{cases} \tag{7.20}$$

$$\begin{cases} \Delta EV^{ets}_t = EV^{ets}_t - EV_t \\ \Delta E\dot{V}^{ets}_t = \Delta EV^{ets}_t / EV_t \end{cases} \tag{7.21}$$

In this chapter, Eq. (7.22) is used to define the absolute and relative change of the household emissions under the carbon-cap or ETS policy in comparison with the carbon tax, where ΔHCE_t^{ets} and $\Delta \dot{HCE}_t^{ets}$ refer to the absolute change and relative change of the household emissions respectively. HCE_t refers to the household emissions in Year t under the carbon tax.

$$\begin{cases} \Delta HCE_t^{ets} = HCE_t^{ets} - HCE_t \\ \Delta \dot{HCE}_t^{ets} = \Delta HCE_t^{ets} / HCE_t \end{cases} \tag{7.22}$$

Scenarios

In this chapter, two schemes are designed to allocate the carbon quotas. In the 2015 and 2005 scheme, the sectoral carbon quotas are set to equal the 2015 and 2005 sectoral emissions in the baseline scenario respectively. As the sectoral emissions in 2015 are generally larger than that in 2005, the sectors will have larger carbon quotas under the 2015 scheme than the 2005 scheme. With the lower targeted emission reduction, sectors are less likely to be subject to the fine price of over-emissions under the 2015 scheme than under the 2005 scheme.

Table 7.1 The Designed Four Scenarios under the Carbon-cap Policy

Scenario	Quota Allocation Scheme	Targeted Emission Reduction
SCRO1	2015 Sectoral Emissions	1% Tax
SCRO2	2015 Sectoral Emissions	2% Tax
SCRO3	2005 Sectoral Emissions	1% Tax
SCRO4	2005 Sectoral Emissions	2% Tax

Note: In these scenarios, the decline factor is assumed to be zero with no carbon trading.

Table 7.1 shows the designed four scenarios to analyse the welfare impacts of the carbon-cap policy compared to the carbon tax. The differences of the scenarios lie in the quota allocation scheme and targeted emission reduction. In Table 7.1, the 1% tax refers to the loose abatement target, whilst the 2% tax denotes the strict abatement target.

Table 7.2 The Designed Four Scenarios with the Different Decline Factors

Scenario	Decline Factor
SCRO3	0%
SCRO5	0.5%
SCRO6	1%
SCRO7	2%

Note: In these scenarios, the carbon quota allocation scheme is assumed to be the 2005 sectoral emissions; the targeted emission reduction is the 1% tax; there is no carbon trading.

Table 7.2 shows the designed four scenarios under the carbon-cap policy where the only difference lies in the decline factor of the free carbon quotas. The quantities of the initially allocated free carbon quotas are of vital importance to the effects of climate policies, according to Li and Jia (2016) who constructed a dynamic recursive CGE model to study the relation between the free quote ratio and ETS price in China. Hence, in this chapter, the comparison among these scenarios will reveal to what extent the decline factor will influence the welfare effects of the carbon-cap policy.

Table 7.3 The Designed Four Scenarios under the Carbon Trading

Scenario	Targeted Emission Reduction	Carbon Trading
SCRO3	1% Tax	No
SCRO4	2% Tax	No
SCRO8	1% Tax	Yes
SCRO9	2% Tax	Yes

Note: In these four scenarios, the carbon quota allocation scheme is assumed to be the 2005 sectoral emissions; the decline factor is zero.

Tables 7.3 shows the designed four scenarios with the differences in the targeted emission reduction and whether the quotas are tradeable or untradeable. Under the carbon-cap policy, the trading of the surplus carbon quotas, namely the carbon trading, is banned while under the ETS policy, the carbon trading is allowed. The comparison among these scenarios will reveal how the targeted emission reduction and carbon trading will affect the welfare effects of the carbon-cap or ETS policy.

Table 7.4 The Designed Four Scenarios under the FCQ Trading

Scenario	Targeted Emission Reduction	Free Carbon Quotas (FCQ)
SCRO8	1% Tax	Tradeable
SCRO9	2% Tax	Tradeable
SCRO10	1% Tax	Untradeable
SCRO11	2% Tax	Untradeable

Note: In these scenarios, the carbon quota allocation scheme is assumed to be the 2005 sectoral emissions; the decline factor is zero; the carbon trading is allowed.

Table 7.4 shows the designed four scenarios under the ETS policy, focusing on the trading of the free carbon quotas. Despite that the free quotas are not allowed to trade in SCRO10 and SCRO11, the paid part of the carbon quotas can be traded in these scenarios.

Model Results

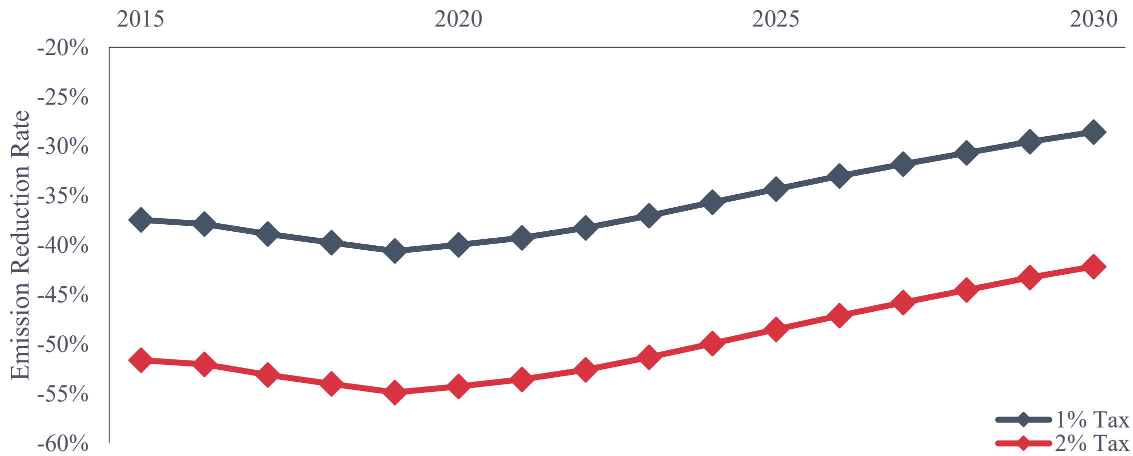


Fig. 7.1 The Targeted Emission Reduction Rate of the Carbon Tax

Fig. 7.1 shows the abatement target of the 1% and 2% tax over time. According to Fig. 7.1, the reduction rate peaked in 2019 and was expected to decrease in 2020–2030. Fig. 7.1 implies that a stricter abatement target will induce higher emission reduction compared to a looser abatement target.

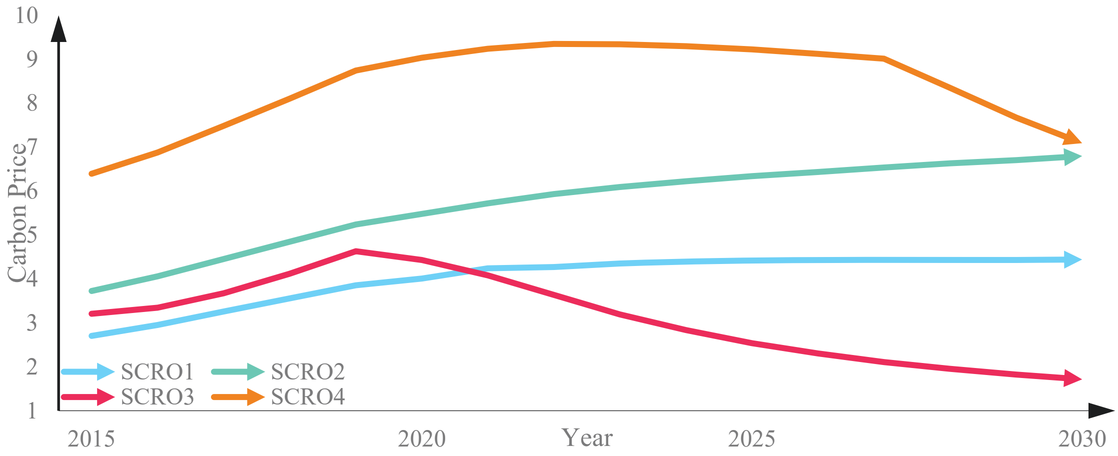


Fig. 7.2 The Carbon Price under the Carbon-cap Policy (Unit: CNY/kg)

Fig. 7.2 shows the equilibrium carbon price in the four scenarios over time. The carbon price in SCRO1 and SCRO2 will remain relatively stable after 2020, whilst the price for SCRO3 and SCRO4 will fluctuate over the studied period. The carbon price in SCRO2 and SCRO4 are higher than that in SCRO1 and SCRO3 respectively, which implies that as the tax rate or targeted emission reduction rises, the carbon price will increase. This is because when the abatement target becomes stricter, the carbon price has to rise in order that the carbon-cap policy will decrease the emissions to the targeted level. This finding complies with Yu, Geng et al. (2018) who used a CGE model to study the impacts of the carbon quota allocation in Shanghai, concluding that a stricter abatement target would lead to a higher carbon price. The carbon price in SCRO4 is higher than that in SCRO2, implying that less initial allocation of the carbon quotas will increase the carbon price at a stricter abatement target. However, this implication is unclear at a looser abatement target because there is no clear relation of the carbon price between SCRO3 and SCRO1 over time.

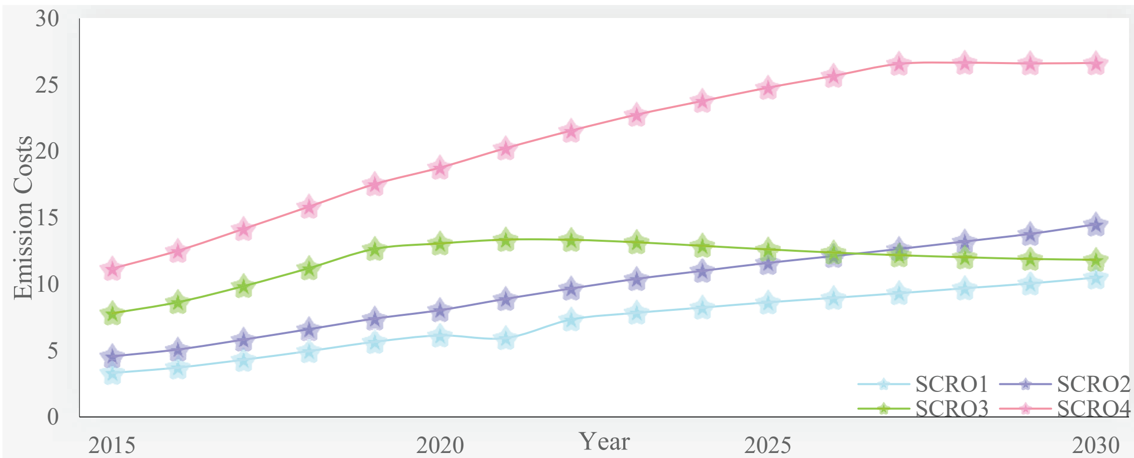


Fig. 7.3 The Overall Emission Costs under the Carbon-cap Policy (Unit: 10^{12} CNY)

Fig. 7.3 shows that over the research period, the emission costs will fluctuate in SCRO2 but increase in the other scenarios except for an outlier. The costs are the highest in SCRO4 and lowest in SCRO1. Noticeably, the curves for the 2015 scheme will grow steadily over time except for a case in

2021 of SCRO1. This outlier is due to the variation of the projected energy consumption. SCRO2 and SCRO4 will have higher costs compared to SCRO1 and SCRO3 respectively, which implies that as the emission reduction increases, the emission costs will increase. SCRO3 and SCRO4 will have higher costs compared to SCRO1 and SCRO2 respectively, which implies that at the same targeted emission reduction, the costs under the 2015 scheme are lower than that under the 2005 scheme. This is because at the same abatement target, a higher allocation of the initial carbon quotas means a lower amount of the targeted emission reduction and thus lower emission costs. This finding complies with the previous research showing that a larger possession of the initial quotas would lead to the lower emission costs for most of the sectors, according to Yu, Geng et al. (2018) who evaluated the macro-economy, carbon markets, and participating sectors in 2030.

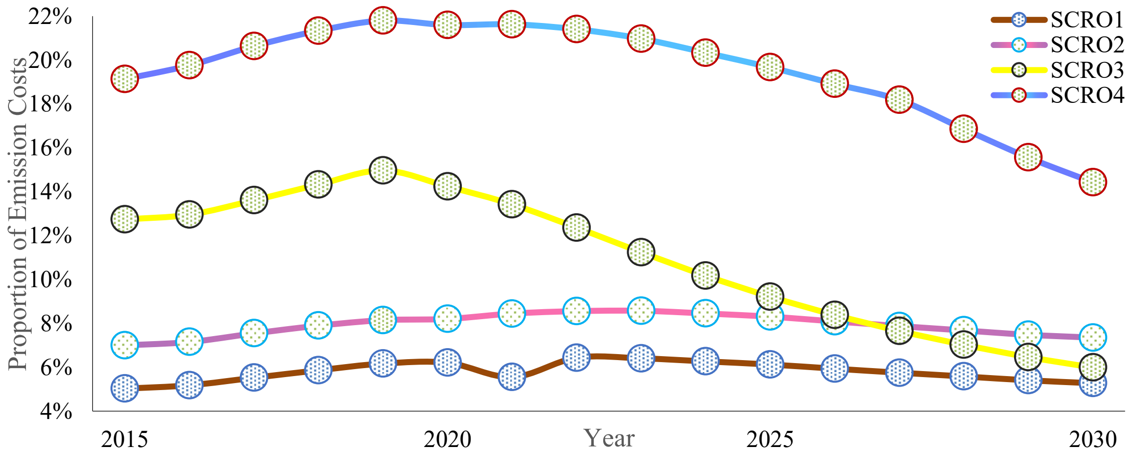


Fig. 7.4 The Proportion of the Overall Emission Costs to the RGDP under the Carbon-cap Policy

Fig. 7.4 shows that the proportion of the emission costs will remain relative stable in SCRO1 and SCRO2, but the proportion will fluctuate dramatically in SCRO3 and SCRO4. SCRO4 will have the highest proportion, whilst SCRO1 will have the lowest proportion. The proportions in SCRO4 and SCRO2 will be higher than that in SCRO3 and SCRO1 respectively. Fig. 7.4 implies that the increase of the targeted emission reduction will raise the proportion of the emission costs to the RGDP. Similar findings could be found in Yang, Teng et al. (2018) who added the carbon tax into the Chinese multi-pollutant abatement planning and long-term benefit evaluation, indicating that the contribution of the mitigation costs to the GDP would rise dramatically as the rate of the carbon mitigation increased. The proportions in SCRO3 and SCRO4 will be higher than that in SCRO1 and SCRO2 respectively, implying that a higher allocation of the carbon quotas will reduce the proportion of the emission costs to the RGDP.

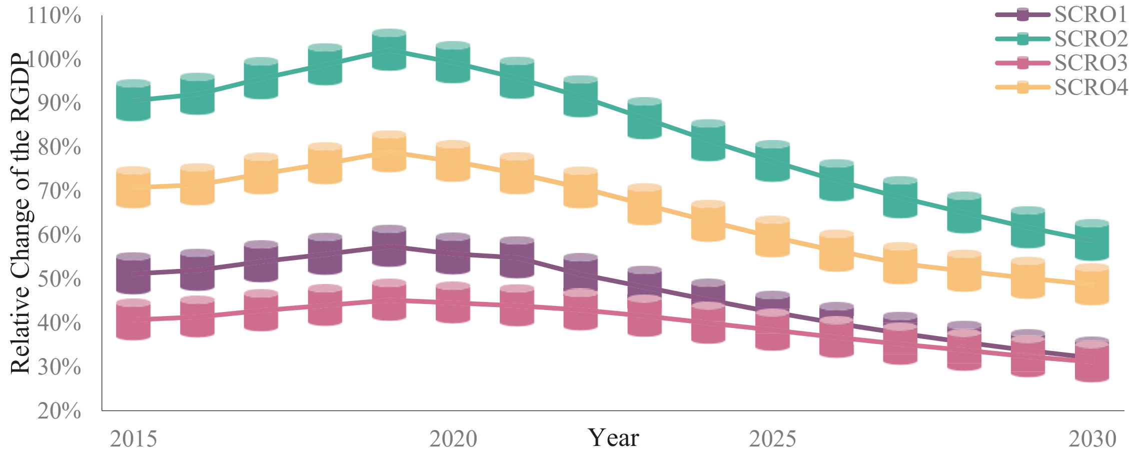


Fig. 7.5 The Relative Change of the RGDP under the Carbon-cap Policy

Fig. 7.5 focuses on the RGDP change shifting from the carbon-cap policy to the carbon tax in the four scenarios over time. The RGDP change will peak in 2019 but decline during 2020–2030. According to Fig. 7.5, the positive RGDP change in the four scenarios implies that compared to the carbon tax, the carbon-cap policy will induce the higher RGDP at the same abatement target. This is because compared to the carbon tax, the carbon-cap policy will give the entities more freedom to adjust their economic activities to meet the abatement target; in other words, the carbon-cap policy intervenes the market mechanism less than the carbon tax. Similarly, Yoon and Jeong (2016) researched better policy options for the emission abatement in the Korean international aviation industry, concluding that the ETS approach was the most efficient of all the designed climate policies in economic terms. Fig. 7.5 also shows that at the same tax rate, the curve for the 2015 scheme will have the higher RGDP than that for the 2005 scheme. This finding complies with the previous research showing that the GDP loss would increase when the abatement target became stricter (Yu, Geng et al. 2018).

Fig. A7.1 in Appendix A shows the absolute change of the RGDP in the four scenarios over time. Different from the relative change of the RGDP, the absolute change will increase as the time goes by. The increase of the targeted emission reduction will reduce the RGDP but expand the RGDP gap between the carbon tax and carbon-cap policy. This finding complies with Wang, Dai et al. (2015) who designed a two-region dynamic CGE model to analyse the economic impacts of the ETS policy in Guangdong province of China, concluding that a stricter carbon constraint would results in more GDP loss.

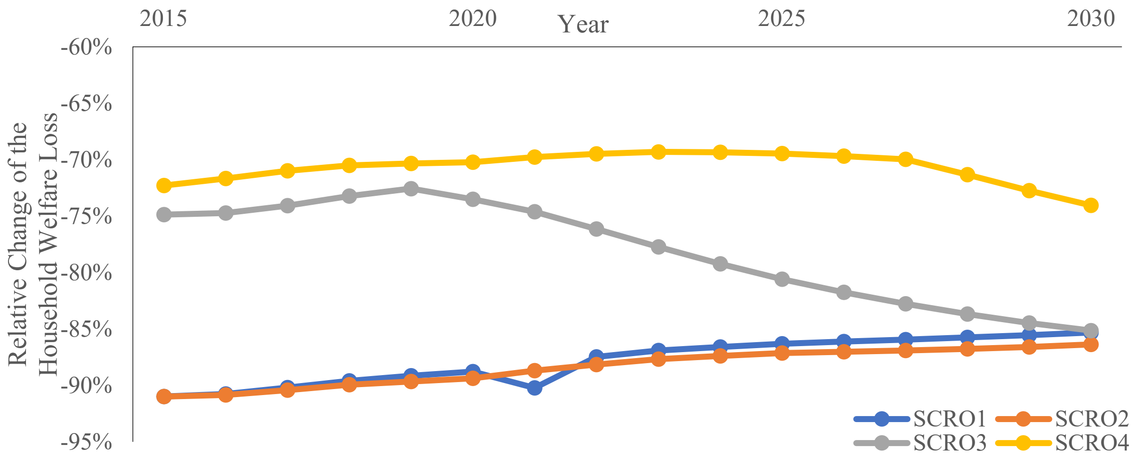


Fig. 7.6 The Relative Change of the Household Welfare Loss under the Carbon-cap Policy

Fig. 7.6 focuses on the household welfare loss change under the carbon-cap policy relative to the carbon tax. According to Fig. 7.6, the carbon-cap policy will induce the lower household welfare loss or higher household welfare compared to the tax. In other words, shifting the carbon tax to the carbon-cap policy with the same targeted emission reduction will increase the household welfare. This is because at the same abatement target, the household income is more flexible in the dynamic transition to the low-carbon economy under the carbon-cap policy compared to the carbon tax.

The 2005 scheme will increase the fluctuation of the household welfare loss over time and the impacts of the targeted emission reduction on the household welfare, compared to the 2015 scheme. In other words, the quantities of the initial carbon quotas will affect the household welfare. Specifically, at a higher quantity of the initial quotas, the policy difference between the carbon tax and carbon-cap policy is relatively stable. This is because the sectors can achieve the abatement target more easily under the carbon-cap policy, and thus the economic expectations under the carbon-cap policy are similar to that under the fixed tax rate. In contrast, a lower quantity of the initial quotas will induce some difficulties in the sectors to achieve the abatement target, and thus the economic expectations are more uncertain under the carbon-cap policy than that under the carbon tax. The uncertainties in the economic expectations could increase the volatility of the effect of the carbon-cap policy on the household welfare.

Fig. 7.6 also shows that a stricter abatement target will reduce the household welfare increase from the policy shifting. This finding corresponds to the previous empirical research showing that the welfare loss caused by the carbon cap would increase at a stricter target (Yu, Geng et al. 2018). Fig. A7.2 in Appendix A shows the absolute change of the household welfare loss over the studied period. The locations of the four curves in Fig. A7.2 imply that the absolute change of the welfare loss will have a very similar trend to the relative change.

Fig. A7.3 and A7.4 in Appendix A shows the absolute and relative change of the household emissions respectively under the carbon-cap policy compared to the carbon tax. The carbon-cap policy will negatively affect the household emissions under the 2015 scheme, but its effect on the 2005 scheme is not clear because the curves for SCRO3 and SCRO4 will fluctuate around the value zero.

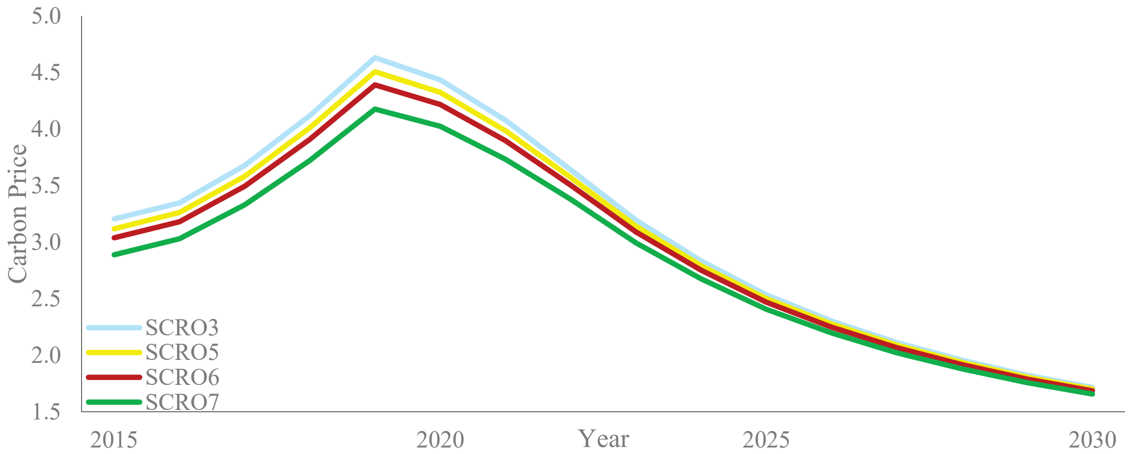


Fig. 7.7 The Carbon Price Influenced by the Decline Factor (Unit: CNY/kg)

Fig. 7.7 shows the variation of the carbon price influenced by the proportion of the free quotas to the allocated carbon quotas over time. The carbon price peaked in 2019 but will decline steadily since 2020. The convergence of the four curves in Fig. 7.7 implies that the decline factor will have a decreasing impact on the carbon price since 2019. The ranking order of the four curves in Fig. 7.7 implies that the quantities of the free quotas are negatively related with the carbon price. The economic intuition underlying Fig. 7.7 is that with more free quotas allocated, the paid part of the carbon quotas will be fewer, and thus an economic entity will buy the quotas at a higher carbon price. This finding agrees with the previous empirical work showing that the annual decline factor would reduce the carbon price (Lin and Jia 2018, Zhang, Li et al. 2018, Wu and Li 2020).

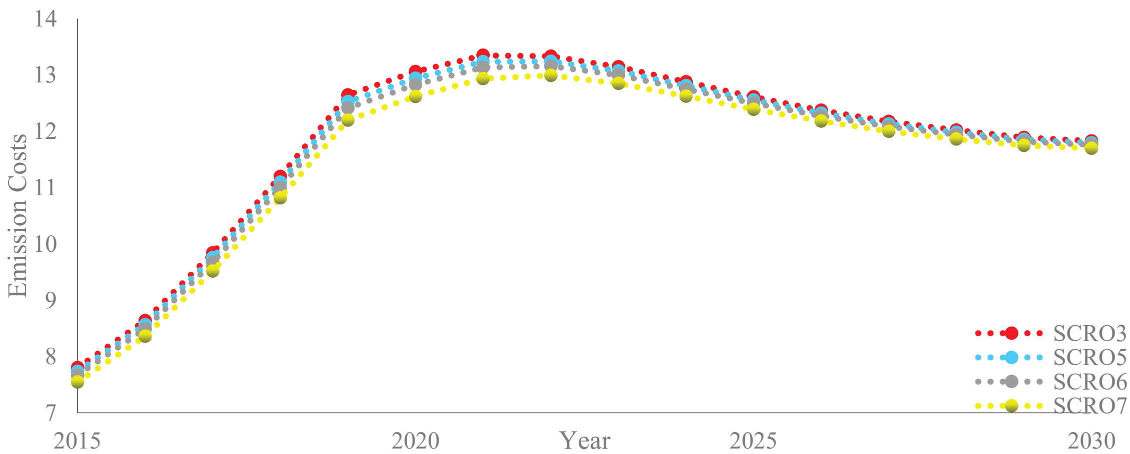


Fig. 7.8 The Overall Emission Costs Influenced by the Decline Factor (Unit: 10^{12} CNY)

Fig. 7.8 shows how the emission costs will vary under the influence of the decline factor of the free quotas in the four scenarios of the 2005 scheme over time. The four curves in Fig. 7.8 increased dramatically in 2015–2019 but will remain stable in 2020–2022 and decrease ever since. Fig. 7.8 implies that the emission costs are positively correlated with the proportion of the free quotas. The rationale of

Fig. 7.8 is that with more free quotas allocated, an economic entity will buy the non-free quotas at a higher carbon price even though fewer quotas will be bought. Fig. A7.5 in Appendix A shows the proportion of the emission costs to the RGDP influenced by the decline factor of the free quotas. According to Fig. A7.5, the cost proportion is also positively related to the free quota proportion, but the peaking time of the curves is slightly earlier than that in Fig. 7.8. This difference could be explained by the different growth rates of the RGDP and emission costs over the studied period.

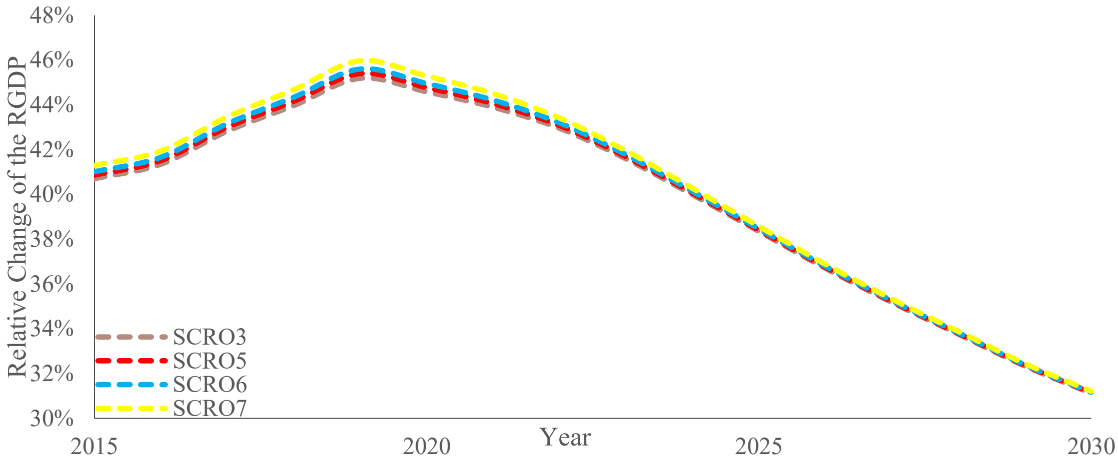


Fig. 7.9 The Relative Change of the RGDP Influenced by the Decline Factor

Fig. 7.9 shows the RGDP change from the carbon tax to the carbon-cap policy influenced by the decline of the free quotas over time. According to Fig. 7.9, the RGDP is positively related to the decline factor, which implies that the decrease of the carbon quotas will induce an economic boom, even though this boom will decline as the time goes by. The reason why the decline factor will increase the RGDP is that fewer free carbon quotas will induce lower emission costs, shown in Fig. 7.8. Fig. A7.6 shows the absolute change of the RGDP influenced by the free quotas over the studied period. Since there exist very minimal differences among the four curves, the decline factor will have almost no impacts on the absolute change.

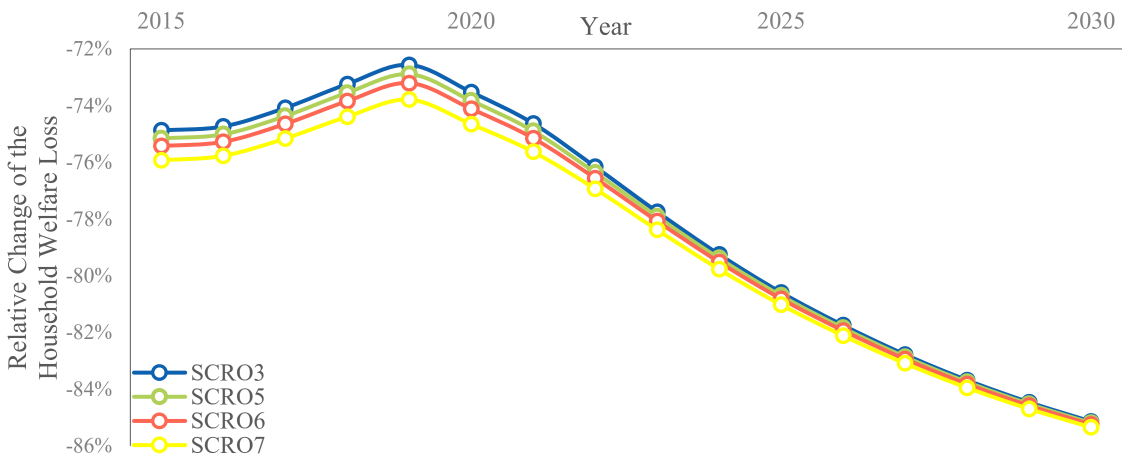


Fig. 7.10 The Relative Change of the Household Welfare Loss Influenced by the Decline Factor

Fig. 7.10 shows the change of the household welfare loss, shifting from the carbon tax to the carbon-cap policy, under the influence of the decline factor over time. The differences among the four curves will decrease in 2020–2030. According to Fig. 7.10, the decline of the free quotas will decrease the welfare loss by less than 2% or slightly increase the household welfare. This is because fewer carbon quotas will induce the lower emission costs and boost the economic growth. Similarly, Li and Jia (2016) used a dynamic recursive CGE model to explore the relationship between the free quota ratio and carbon price, empirically showing that the ratio of the free quotas was negatively related to the resident utility. Fig. A7.7 in Appendix A shows how the decline factor will affect the absolute change of the household welfare loss. According to Fig. 7.7, the decline factor will have minimal impacts on the absolute change of the welfare loss.

Fig. A7.8 and A7.9 in Appendix A show the absolute and relative change of the household emissions to the carbon tax respectively influenced by the decline factor over time. The convergence of the four curves in Fig. A7.8 and Fig. A7.9 implies that the decline factors will have almost no impacts on the absolute and relative change of the household emissions.

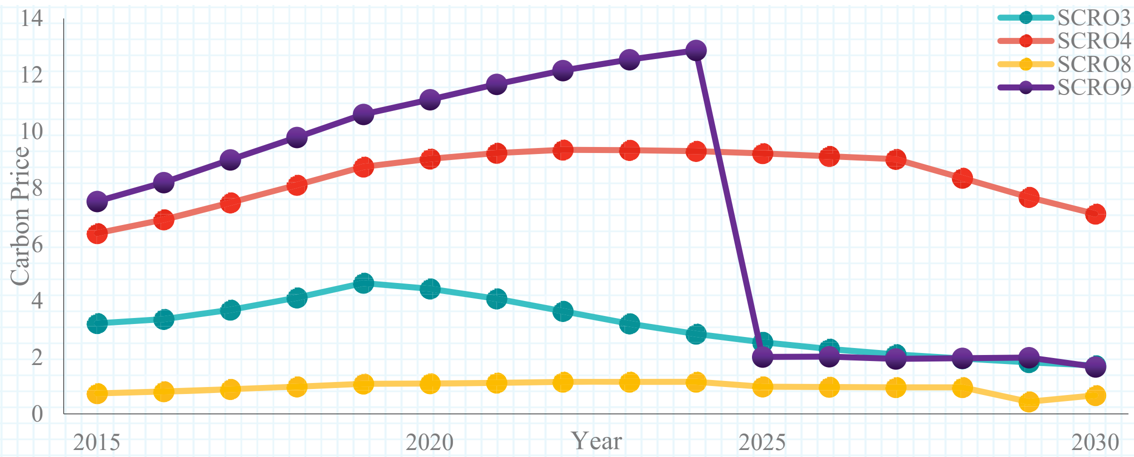


Fig. 7.11 The Carbon Price under the Carbon Trading (Unit: CNY/kg)

Fig. 7.11 shows the differences of the carbon price between the carbon-cap and ETS policy. The carbon price in SCRO8 will be lower than that in SCRO3, implying that allowing the carbon trading will decrease the carbon price at a looser abatement target. However, at a stricter abatement target, allowing the carbon trading will increase the carbon price in 2015–2024 but decrease the price in 2025–2030. Noticeably, the curve for SCRO9 will decrease dramatically in 2014–2025, and the sudden drop is explained in Fig. 7.17. The positive impact of the carbon trading on the carbon price can be explained by the coverage of the fine price: since less sectoral emissions are subject to the fine price of the over-emissions under the ETS policy, the carbon price will rise to compensate the loss of the emission reduction induced by the tightening of the targeted scope of the fine price; otherwise, the same reduction target cannot be achieved. In contrast, the negative impact of the carbon trading can be explained by the economic intuition that the carbon trading gives more flexibility to the carbon market, and thus the economic entity in demand for the carbon quotas could buy the quotas from the market at a lower price.

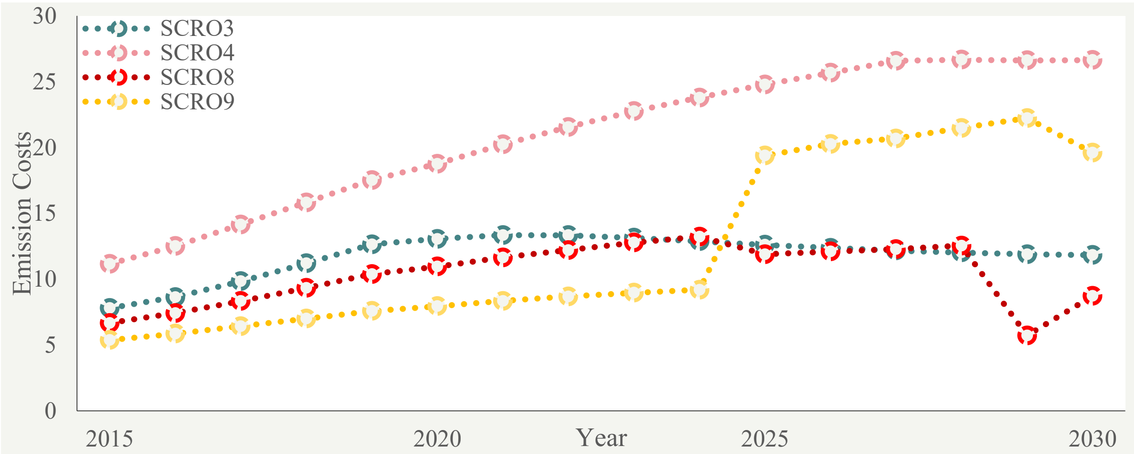


Fig. 7.12 The Overall Emission Costs under the Carbon Trading (Unit: 10^{12} CNY)

Fig. 7.12 shows the differences of the emission costs between the carbon-cap and ETS policy over the studied period. At the target of the 1% tax, the carbon trading will slightly change the costs except for a dramatic decrease in 2029–2030. However, at the target of the 2% tax, the ETS policy will significantly reduce the costs over time, even if the carbon price will increase in 2015–2024, shown in Fig. 7.11. The reason why the carbon trading will decrease the emission costs is that the market allocates the carbon quotas more efficiently than the governmental instructions, and thus the emission costs will be lower under the market mechanism. Similarly, Liu and Wei (2016) used a multiregional general equilibrium model to assess the impacts of a joint Europe-China ETS, concluding that the carbon trading would reduce the overall emission costs of the participants. Fig. A7.10 in Appendix A shows the proportion of the emission costs to the RGDP influenced by the carbon trading over time. Fig. A7.10 implies that the proportion of the emission costs will have a very similar trend to the emission costs under the impact of the carbon trading.

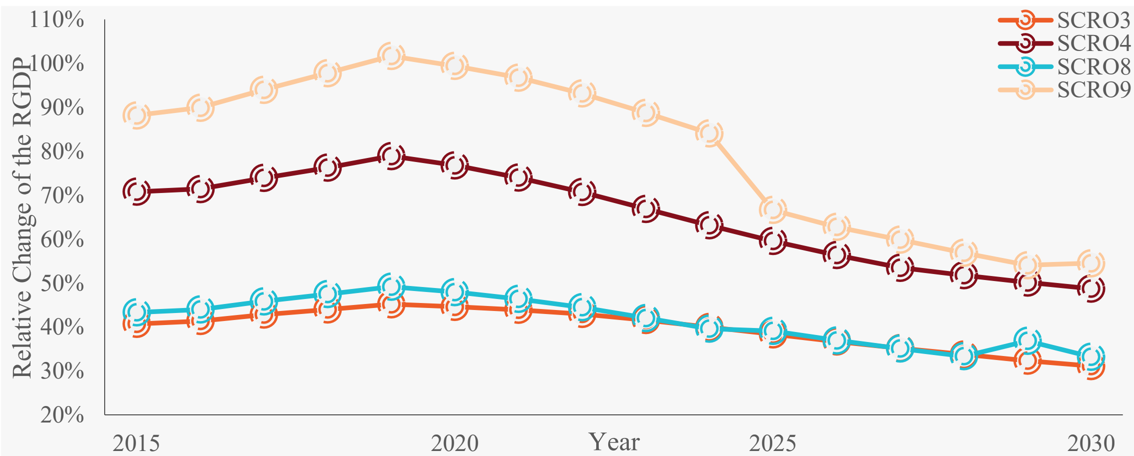


Fig. 7.13 The Relative Change of the RGDP under the Carbon Trading

Fig. 7.13 shows how the carbon trading will affect the RGDP change under the carbon-cap and ETS policy relative to that under the carbon tax over time. At the target of the 1% tax, the carbon trading will only slightly increase the RGDP. By comparison, at the target of the 2% tax, the carbon trading will significantly increase the RGDP even though this impact will diminish in 2025–2030. Fig. 7.13 implies that the carbon trading under the ETS policy will increase the RGDP compared to the carbon-cap policy. This is because the carbon trading gives economic entities more freedom to meet the abatement target; hence, the sectors can make better production choices under the carbon trading. Similar findings can be found in the previous empirical work by Yu, Geng et al. (2018) and Cheng, Dai et al. (2016). Fig. A7.11 in Appendix A shows the absolute change of the RGDP between the carbon-cap and ETS policy. Fig. A7.11 implies that the impact of the carbon trading on the RGDP absolute change is similar to that on the RGDP relative change.

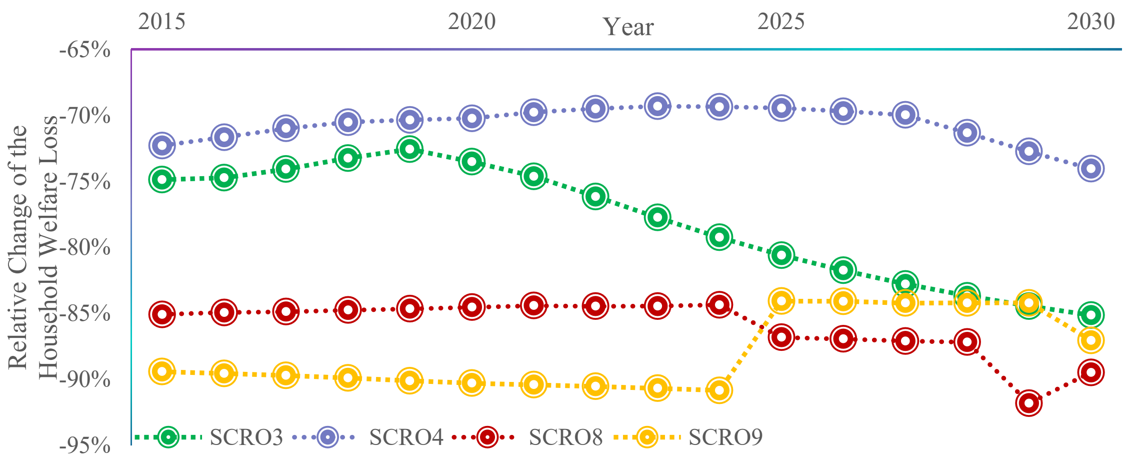


Fig. 7.14 The Relative Change of the Household Welfare Loss under the Carbon Trading

Fig. 7.14 shows the impact of the carbon trading on the relative change of the household welfare loss over the studied period. As the curves for SCRO8 and SCRO9 are below that for SCRO3 and SCRO4, implying that the carbon trading will decrease the household welfare loss compared to that under the carbon-cap policy. This is because the carbon trading will increase the sectoral output, and thus the household may gain more labour income. Similarly, Yu, Geng et al. (2018) who used a CGE model to predict the future impacts of the carbon cap-and-trade policy in Shanghai, concluding that the carbon trading would alleviate the welfare loss caused by the carbon-cap policy. Fig. A7.12 in Appendix A shows the absolute change of the household welfare loss under the carbon-cap and ETS policy compared to the carbon tax. Fig. A7.12 implies that the absolute change of the household welfare loss will have a very similar trend to the relative change.

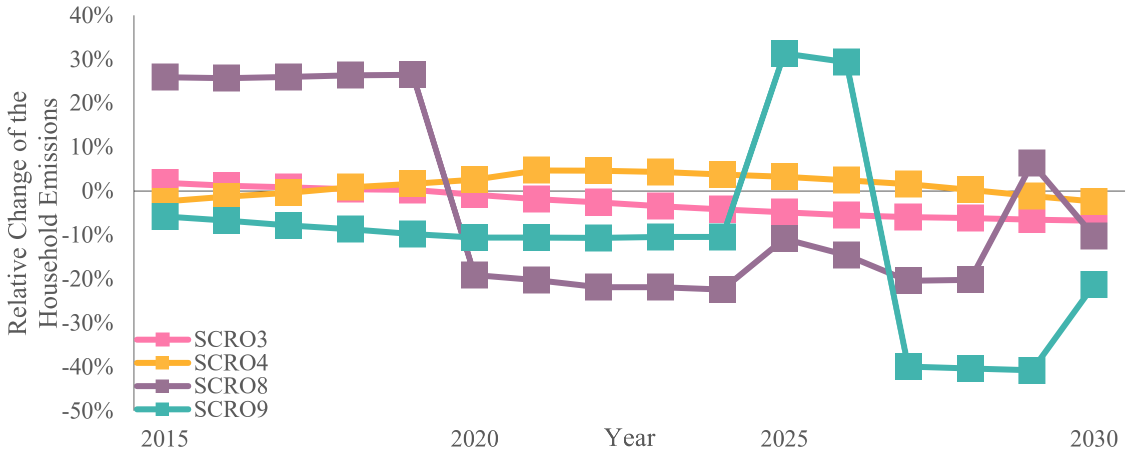


Fig. 7.15 The Relative Change of the Household Emissions under the Carbon Trading

Fig. 7.15 shows how the carbon trading will affect the household emission change under the carbon-cap and ETS policy relative to that under the carbon tax. The curves for SCRO8 and SCRO9 are much more volatile than that for SCRO3 and SCRO4, implying that the household emissions will fluctuate more in the 2005 scheme than that in the 2015 scheme. In 2020–2030, the curves for SCRO8 and SCRO9 are generally below the curves for SCRO3 and SCRO4 except for a few outliers, owing to the variation of the projected data. The projections in the 2015 scheme imply that the carbon trading will have a minimal impact on the household emissions in the future. This finding complies with Ju and Kiyoshi (2019) who employed an input-output model to analyse the cost transmission of the ETS policy in China, indicating that the increase rate of the household consumption in most sectors would be below 0.1%, and thus the household emissions might not change significantly. In contrast, the projection in the 2005 scheme implies that the carbon trading will generally have a negative impact on the household emissions. This finding corresponds to the potential effects of the ETS policy on improving the energy structure (Tang, Shi et al. 2016) and promoting the output of the renewable energy (Yu, He et al. 2017). Fig. A7.13 in Appendix A shows the absolute change of the household emissions under the carbon-cap and ETS policy. Fig. A7.13 implies that the carbon trading will have a very similar impact on the absolute change of the household emissions to the impact on the relative change.

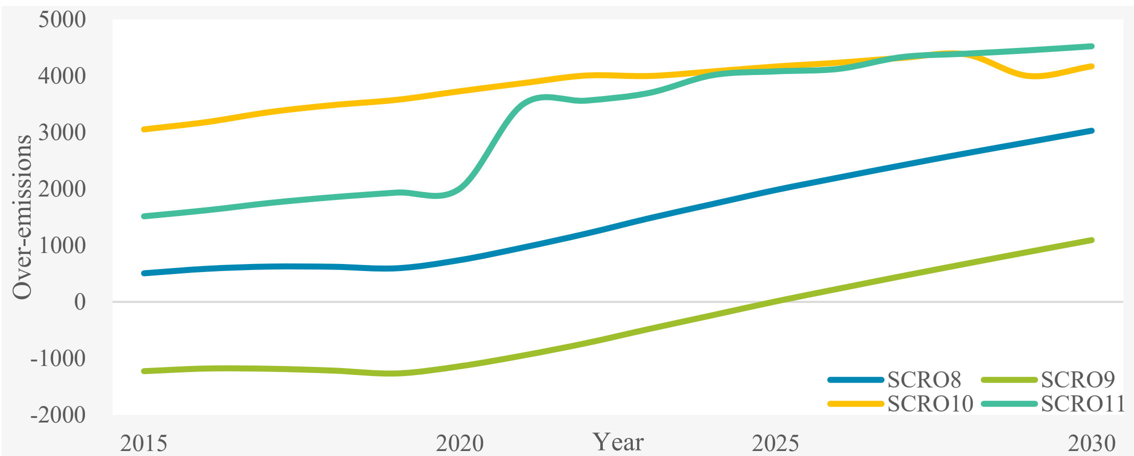


Fig. 7.16 The Over-emissions under Banning the FCQ Trading (Unit: 10^6 tonne)

Fig. 7.16 shows the over-emissions that cannot be covered by the ETS policy in the four scenarios over the studied period. At the target of the 1% tax, the overall sectoral emissions will exceed the overall carbon quotas irrespective of trading the free carbon quotas (FCQ). Hence, banning the FCQ trading will not affect the application of the fine price, and thus it will have almost no impacts on the ETS policy effects. However, the situation is different at the target of the 2% tax: without the FCQ trading, the over-emissions will be positive over time, implying that the overall tradeable carbon quotas cannot cover the summation of the sectoral over-emissions. In contrast, with the FCQ trading, the summed sectoral emissions are less than the summed carbon quotas in 2015–2024, but the situation will change in 2025–2030. Fig. 7.16 implies that at a stricter abatement target, banning the FCQ trading will influence the application of the fine price and thus ETS policy effects.

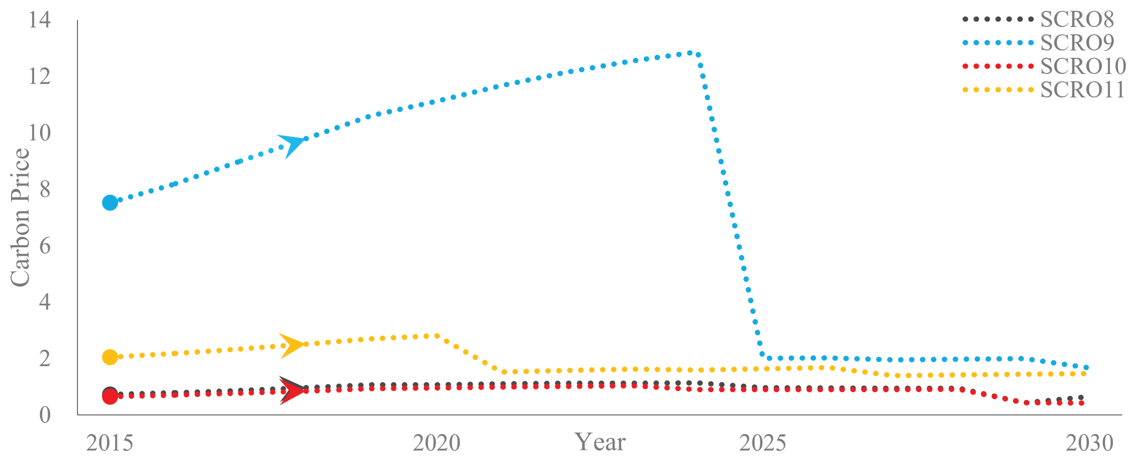


Fig. 7.17 The Carbon Price under Banning the FCQ Trading (Unit: CNY/kg)

Fig. 7.17 shows the variation of the carbon price under the ETS policy where the FCQ trading is allowed and disallowed. At the target of the 1% tax, banning the FCQ trading will only slightly reduce the carbon price; however, this impact is minimal. At the target of the 2% tax, banning the FCQ trading will have a much more significantly negative impact on the carbon price. The sudden drop of the carbon price in 2024–2025 in SCRO9 can be explained by the applying of the fine price. According to Fig. 7.16, the over-emissions will become positive in 2025, which means that not all the sectoral emissions can be absorbed by the carbon quotas. The applying of the fine price will reduce the carbon price since the sectoral emissions begin to be regulated by the fine price.

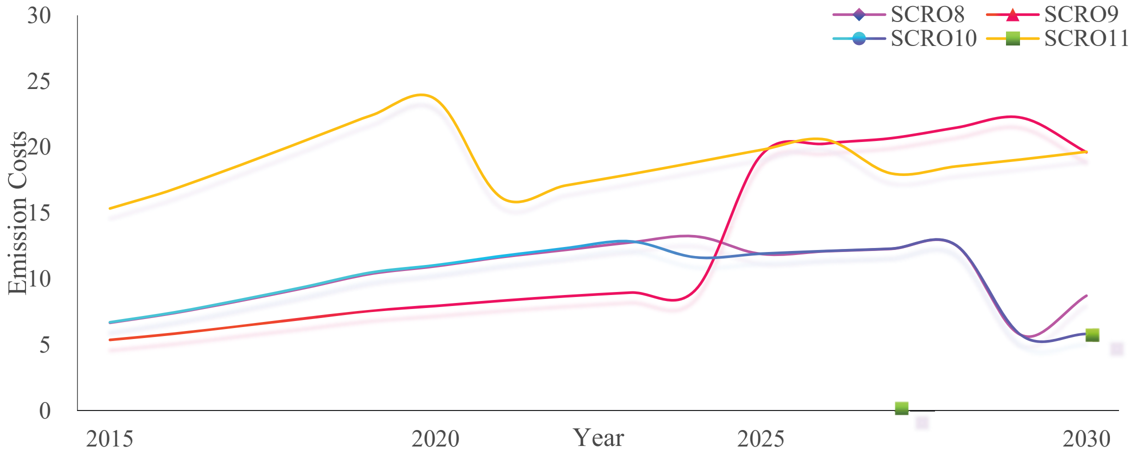


Fig. 7.18 The Overall Emission Costs under Banning the FCQ trading (Unit: 10^{12} CNY)

Fig. 7.18 shows the emission costs under the impact of the FCQ trading over the studied period. At the target of the 1% tax, banning the FCQ trading will have almost no impacts on the emission costs except for the two outliers, owing to the variation of the projected data. In contrast, banning the FCQ trading will increase the costs in 2015–2026, decrease the costs in 2027–2029, and have no impact in 2030 at the target of the 2% tax. Fig. 7.18 implies that at a stricter abatement target, banning the FCQ trading will increase the costs in the short term but decrease the costs in the long term. This is because the strict emission abatement directly soars the costs of energy consumption; however, the induced technical progress or development of renewable energy will decrease the emission costs in the long term. Similar evidence can be found in Hagem (2003) who used a two-period model to explore how the tradeable or untradeable free quotas would affect the investment in new abatement technology, concluding that the grandfathering rule of the untradeable quotas helped the firms develop new abatement technology to reduce the emission costs. Fig. A7.14 in Appendix A shows the proportion of the emission costs to the RGDP influenced by banning the FCQ trading. The curves in Fig. A7.14 have very similar implications to the curves in Fig. 7.18.

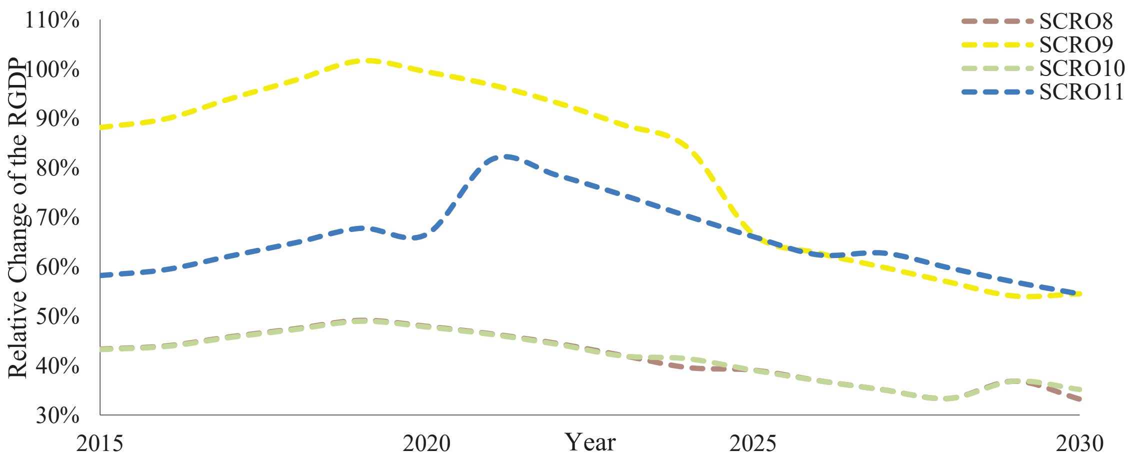


Fig. 7.19 The Relative Change of the RGDP under Banning the FCQ Trading

Fig. 7.19 shows the RGDP change under the impact of the FCQ trading over the studied period. At the target of the 1% tax, banning the FCQ trading will have almost no impacts on the RGDP change except that it will slightly increase the RGDP in 2024 and 2030. However, at the target of the 2% tax, banning the FCQ trading will decrease the RGDP in 2015–2024, have no impact in 2025–2026, and increase the RGDP by approximately 5% in 2027–2030. Fig. 7.19 implies that at a stricter abatement target, banning the FCQ trading could decrease the RGDP in the short term but have a positive impact in the long term. This is because a strict abatement target may adversely affect the economy by soaring the costs of energy consumption; however, the strict target could facilitate the dynamic transition to the low-carbon economy and thus generate economic benefits. Similarly, Bartels and Musgens (2008) analysed the effects of freely allocating carbon quotas to new power plants in the EU ETS market, concluding that the free allocation distorted the investments and hampered the efficiency of the ETS policy. Fig. A7.15 in Appendix A shows the absolute change of the RGDP influenced by banning the FCQ trading. The RGDP absolute change will have very similar implications to the RGDP relative change.

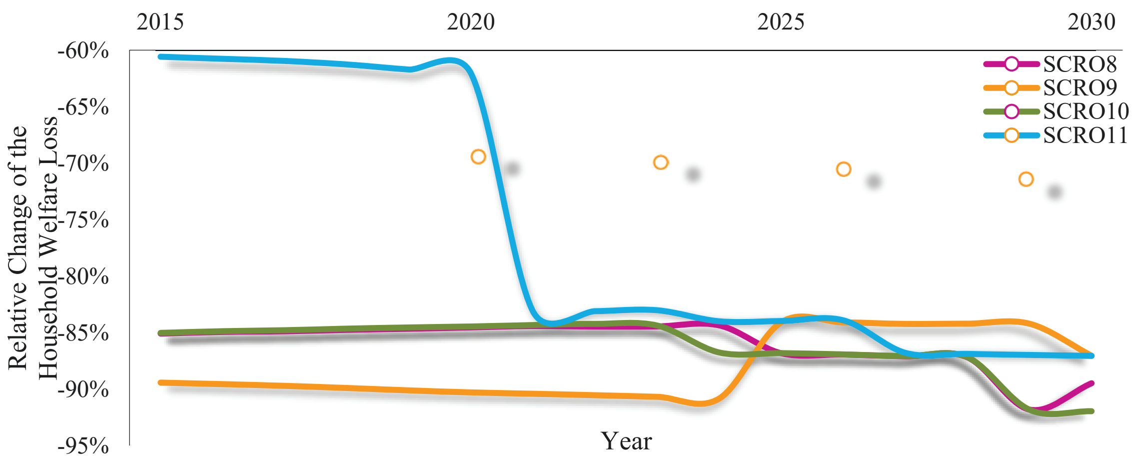


Fig. 7.20 The Relative Change of the Household Welfare Loss under Banning the FCQ Trading

Fig. 7.20 shows how banning the FCQ trading will affect the household welfare loss under the ETS policy over time. At the target of the 1% tax, banning the FCQ trading will have minimal impacts on the welfare loss except that it will slightly decrease the loss in 2024 and 2030. At the target of the 2% tax, there is a sharp decrease of the welfare loss in 2020–2021 in SCRO11, but considering this decrease, the welfare loss in SCRO11 will still surpass that in SCRO9. In 2027–2029, banning the FCQ trading will decrease the welfare loss by approximately 3% in SCRO11 compared to SCRO9, and the two curves will be almost at the same level in 2030. Fig. 7.20 implies that at a stricter abatement target, banning the FCQ trading decreases the household welfare at an initial stage, but it will increase the welfare in a more sophisticated ETS market. This is because the household will pay more energy costs when the FCQ trading is banned; however, in the long term, the induced technical progress or development of renewable energy will decrease the energy costs for the household. This finding agrees with Golombek and Hoel (2008) who adopted a static research framework to endogenously define abatement technologies, concluding that the welfare would be lower when the carbon trading was permitted than when it was not. Fig. A7.16 in Appendix A shows the absolute change of the household welfare loss under banning the FCQ trading. Fig. A7.16 implies that the absolute change of the household welfare loss will have an identical trend to the relative change.

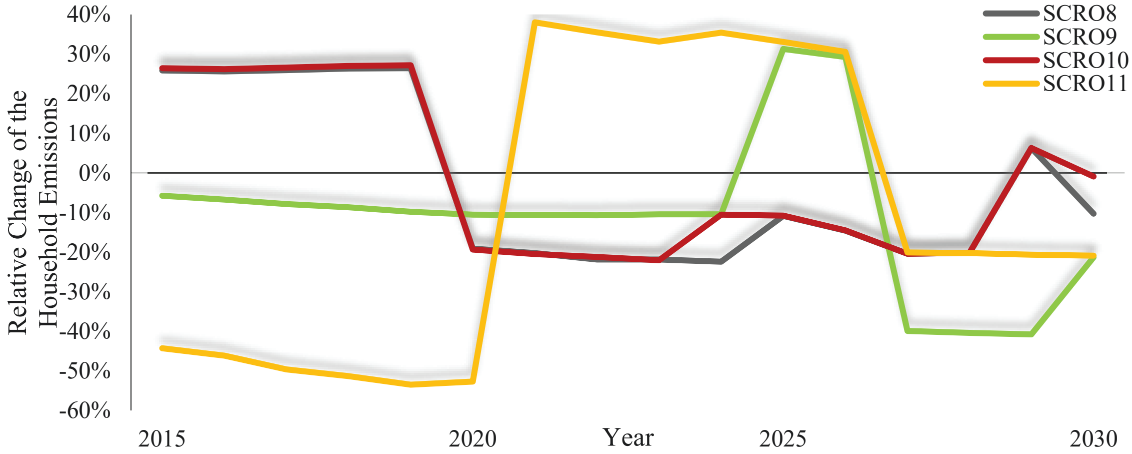


Fig. 7.21 The Relative Change of the Household Emissions under Banning the FCQ Trading

Fig. 7.21 shows how banning the FCQ trading will affect the relative change of the household emissions under the ETS policy compared to the carbon tax. At the target of the 1% tax, banning the FCQ trading will have almost no impact on the household emissions except for a slight reduction in 2024 and 2030. In contrast, at the target of the 2% tax, banning the FCQ trading decreased the household emissions in 2015–2020, and then it will increase the emissions until 2030 where the two curves will converge. Fig. 7.21 implies that at a stricter abatement target, banning the FCQ trading may decrease the household emissions in the short term but increase the emissions in the long term. This is because banning the FCQ trading curbs the household energy consumption owing to the rising energy costs and induced economic recession; however, in the long term, it will decrease the energy costs and boost the economic growth and thus increase the household energy consumption. Fig. A7.17 in Appendix A shows the absolute change of the household emissions influenced by banning the FCQ trading. According to Fig. A7.17, the absolute change of the household emissions will have a very similar trend to the relative change.

Recycling the revenues of the carbon-cap or ETS policy, under the 2005 and 2015 quota allocation schemes, will minimally influence the effects of the carbon-cap or ETS policy. This is because the policy revenues are quite small compared to the induced RGDP change and household welfare loss. This result is quite similar to the minimal policy effects of recycling the tax revenues shown in Chapter 1.

In the INDC (NDRC 2015), China has pledged to lower its carbon emissions per unit of the GDP by 60% to 65% from the 2005 level by 2030. The 2005 carbon intensity is calculated as 0.31 (2015 price), basing on the sectoral energy consumption data from 2016 China Energy Statistical Yearbook (NBS 2016) and sectoral output data from 2005 China Input-Output Table (NBS 2005).

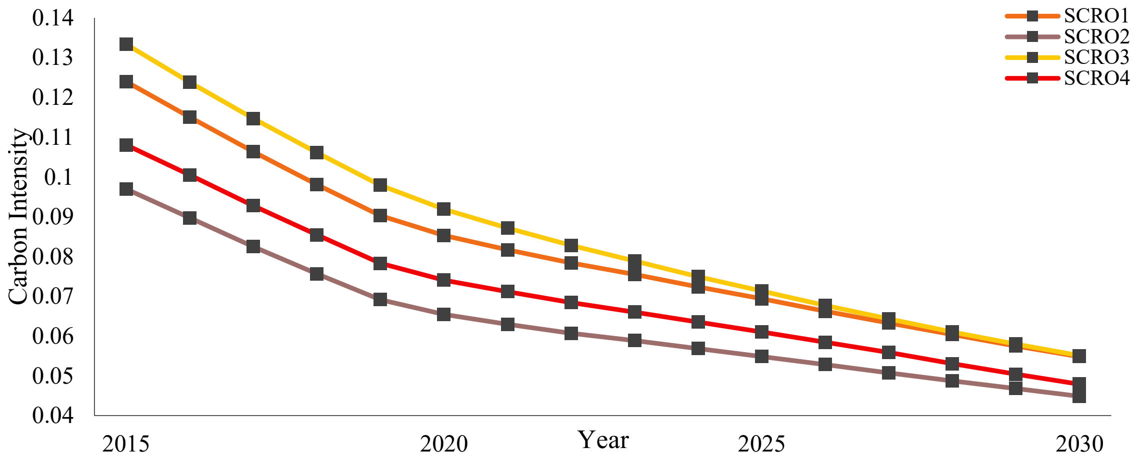


Fig. 7.22 The Carbon Intensity under the Carbon-cap Policy (Unit: kg/CNY)

Fig. 7.22 shows the projected carbon intensity under the carbon-cap policy in the four scenarios over the studied period. The 2030 carbon intensity in the four scenarios will be much lower than 60% of the 2005 level, implying that the designed carbon-cap policy will help China meet the INDC target of the carbon intensity reduction. The curves for SCRO3 and SCRO4 are above the curve for SCRO1 and SCRO2, implying that a higher allocation of the carbon quotas will increase the carbon intensity. The curves for SCRO2 and SCRO4 are below the curve for SCRO1 and SCRO3, implying that a stricter target of the emission reduction will decrease the carbon intensity. However, the differences among the curves will diminish as the time goes by.

Fig. A7.18 in Appendix A shows how the decline factor of the free quotas will affect the carbon intensity. According to Fig. A7.18, the decline factor will have very limited impacts on the carbon intensity. Fig. A7.19 in Appendix A shows the impacts of the carbon trading on the carbon intensity. According to Fig. A7.19, at a looser target of the emission reduction, the carbon trading will have almost no impacts on the carbon intensity; however, at a stricter target, the carbon trading will reduce the carbon intensity. Fig. A7.20 in Appendix A shows the carbon intensity influenced by banning the FCQ trading. According to Fig. A7.20, at a looser target, banning the FCQ trading will have almost no impacts on the carbon intensity; in contrast, it will increase the carbon intensity in 2015–2024 but have no impacts in 2025–2030.

Discussion

In this chapter, the carbon-cap or ETS policy is simulated to have the same emission effect but different welfare effects, compared to the carbon tax. Theoretically, the carbon-cap or ETS policy is equivalent to the carbon tax because both policies set a carbon price for emitting greenhouse gases (Allan, Lecca et al. 2014). Hence, it is meaningful to compare the welfare effects of the ETS policy and carbon tax at the same abatement target.

The carbon price is regarded as the marginal costs to achieve the required emission reduction, according to Wu, Dai et al. (2016) who used a static CGE model to evaluate the economic impacts of the ETS policy in Shanghai. Generally, previous researchers agreed that the carbon price is positively related to the reduction amount of the carbon emissions. For example, Yu, Fan et al. (2020) modelled the ETS policy from an agent-based perspective based on the European data, indicating that when the abatement target was low, the carbon price would drop to zero; when the abatement target was high, the carbon price would stay high. Similarly, Wang, Dai et al. (2015) employed a two-region dynamic CGE model to assess the ETS impacts in Guangdong Province of China, concluding that the more the reduction rate was, the higher the carbon price would be. The mechanism of the emission reduction driving the carbon price is that a stricter abatement target would reduce the volume of the circulating quotas in the market and thus boost the price (Yu, Geng et al. 2018).

At the given abatement target, the carbon price will vary if the carbon quotas become tradeable. This chapter empirically shows that the carbon trading will decrease the carbon price at the target of the 1% tax and in 2025–2030 at the target of the 2% tax. This finding agrees with Wu, Dai et al. (2019) who utilised a CGE model to investigate the impacts of achieving Taiwan's INDC target, concluding that the shadow prices of most sectors in the cap-without-trade scenarios were higher than the actual carbon price in Taiwan.

Banning the FCQ trading will decrease the carbon price. This finding disagrees with the previous study on the enterprise behavior of the optimal use of the carbon quotas (Brechet, Tsachev et al. 2012). Banning the FCQ trading could induce the non-optimal use of the FCQ at the enterprise level, which might increase the market price for the tradeable quotas (Brechet, Tsachev et al. 2012). The result difference lies in the model assumptions: Brechet, Tsachev et al. (2012) analysed the carbon quotas mainly basing on the market mechanism but neglected the induced effects of banning the FCQ trading. In contrast, the comprehensive CGE model in this chapter not only quantifies the market mechanism but also measures the induced effects, including the technological progress. In the literature, the ETS impacts on the technological progress was confirmed in Zhou, Liang et al. (2020) who used the difference-in-difference-in-difference (DDD) model to evaluate the ETS impacts in China.

Interestingly, the carbon price analysed in this chapter is not linearly correlated with the emission costs, because the carbon price will affect the effort of the emission reduction. I have empirically found that the costs are influenced by the allocation scheme of the carbon quotas. The more quotas are given to a sector, the less emission costs the sector will have. Similarly, Wu, Dai et al. (2016) compared the carbon cap policy with the ETS policy in Shanghai under the INDC target, concluding that the average costs would almost double in 2020–2030 owing to the increasingly stricter carbon cap.

The emission costs will be affected by the quantities of the free quotas under the chosen scheme of the allocated quotas. I have empirically found that the costs will be reduced by the decline factor of the free quotas. Conversely, Lin and Jia (2018) used a dynamic recursive CGE model to study the impacts of the ETS quota decline scheme in China, empirically showing that the emission costs would be higher in the scenarios with the high decline factors. The policy coverage may explain this result difference. Only a few sectors were covered in Lin and Jia (2018) who did not consider and calculate the future carbon emissions of the noncovered sectors. By comparison, in this chapter, almost all the sectors are covered by the carbon-cap policy except for the electricity subsectors exploiting renewables only.

The decline factor of the free quotas will increase the RGDP or decrease the RGDP loss induced by the carbon-cap and ETS policy. This finding disagrees with Wu and Li (2020) who used a dynamic recursive CGE model to analyse the economic and environmental impacts of the quota allocation in China, indicating that the higher the free allocation ratio was, the lower the GDP loss was and thereby the greater the GDP would be. The result difference between this chapter and Wu and Li (2020) lies in the assumption of the projected GDP growth rate: the real GDP in this chapter is assumed to grow at the given rate by OECD (2018), whilst the GDP growth rate was endogenously determined and also affected by the decline factor in Wu and Li (2020).

The carbon trading will increase the RGDP, and this evidence could be found in many previous studies. For example, Wu, Dai et al. (2016) used a static CGE model to empirically show that with the help of the emission trading, the GDP loss, induced by the mitigation policy, of Shanghai would change by 0.9% instead of 1.0% in 2020 and 1.6% instead of 1.7% in 2030; Wang, Dai et al. (2015) used a two-region dynamic CGE model to empirically show that the ETS could reduce the mitigation costs at both the sectoral level, such as the sectoral output, and the macro level, such as the GDP; Qi and Weng (2016) used a multi-regional CGE model to ambitiously design a global ETS market, which increased the economic aggregate of the participating countries.

The ETS impact on the household welfare is different from that on the RGDP. This chapter empirically shows that the decline factor of the free quotas will increase the household welfare. This finding disagrees with Lin and Jia (2018) and Zhang, Li et al. (2018) who argued that the higher decline factor would decrease the household welfare. This result difference mainly lies in the assumption on the ETS revenues: the government transferred the ETS revenues to the household in Lin and Jia (2018) and Zhang, Li et al. (2018). In contrast, the ETS revenue recycling is not considered in this chapter. This is because approximately 90% of the allocated carbon quotas are free, and the revenues of the 10% quotas are quite small compared to the values of the macroeconomic variables in this chapter.

The carbon trading will increase the household welfare. This evidence could be found in Wu, Dai et al. (2019) who used a CGE model to analyse the effects of the ETS policy in Taiwan, showing that the consumption loss, caused by the carbon-cap policy, diminished under the ETS policy, and the reduction of the consumption loss would increase the household welfare. This positive impact can be explained by the income increase resulting from the RGDP growth induced by the carbon trading.

Although the sectoral emissions under the ETS policy are set to equal that under the carbon tax, the household emissions are directly affected by the amount of the targeted emission reduction. This is because compliance with the cap would increase the costs of the fossil fuel generation as well as the benefits of exploiting the renewable energy, according to Bird, Holt et al. (2008) who explored the policy options to enable the carbon markets and renewable energy markets to work together. As the household consumption of the fossil fuels occupies a significant proportion to the overall household energy consumption, the ETS policy will affect the household emissions via its impact on the nonrenewable energy consumption.

To summarise, the empirical results of this chapter fit well with the literature even though some result differences exist owing to the model assumptions. With the same amount of the targeted emission reduction, the ETS policy will induce the higher household welfare, compared to the carbon tax, even though the ETS policy will still generate the net welfare loss, compared to the baseline scenario. Since the evaluation of the ETS policy is mainly based on the welfare effect, how effective the ETS policy is to reduce the emissions is beyond the research scope of this chapter. The designed carbon price of the ETS scenario in Li and Jia (2017) was 100 CNY/t CO_2, equivalent to 0.1 CNY/kg CO_2. Similarly, the highest carbon price in Lin and Jia (2017) ranged from 32.5–57.2 USD/t CO_2, equivalent to 0.2–0.4 CNY/kg CO_2, using the 2015 exchange rate from USD to CNY according to NBS (2017). In contrast, the carbon price in the SCRO3 of this chapter ranges from 1.7–3.2 CNY/kg CO_2, much higher than the previous research.

In the reality, the carbon price of the ETS market may not reach the simulated level in this chapter. This is because the exorbitant price may induce some covered sectors to be overwhelmed (Lin and Jia 2017). Although a strict ETS policy with a high carbon price could facilitate the creation of a low-carbon supply chain (Wang, Yang et al. 2020), it might lead to insufficient funds for technological upgrading and even bankruptcies (Chen, Yuan et al. 2020). Conversely, a low carbon price would undermine the capacity of the ETS market to reduce the emissions, because it had little impacts on the energy consumption (Lin and Jia 2019) and was not beneficial to low carbon technological innovations and economic structure reshaping (Chen, Yuan et al. 2020). Hence, a medium carbon price is more rational because it motivates market transactions and benefits low-carbon technological innovations (Chen, Yuan et al. 2020).

To overcome the overwhelming carbon pricing under the ETS policy, a potential complementary study lies in analysing the ETS impacts on the emission reduction assuming the equal welfare impacts. In the complementary study, the ETS carbon pricing is directly linked to the welfare effects of the carbon tax. As the carbon tax may not severely harm the economic output, the ETS carbon pricing could be reasonable. Perhaps, this chapter and the potential complementary study altogether may comprehensively reveal whether the carbon tax or ETS policy is preferable.

Policy Implication

The results of this chapter imply that fewer quantities of the carbon quotas will induce the higher emission costs and thus harm the economic growth. However, for the allocated carbon quotas, the government should give less free quotas, which will reduce the carbon price and emission costs as well as boom the economic growth and increase the household welfare. At a looser target of the emission reduction, the carbon trading will reduce the carbon price and increase the household welfare, but its impact on the RGDP is not distinct. The untradeable free quotas will have very limited impacts on the emission costs or welfare, compared to the tradeable free quotas, even though banning the FCQ trading will increase the over-emissions. In contrast, at a stricter target, the carbon trading will increase both the RGDP and household welfare but decrease the emission costs. Banning the FCQ trading will increase the emission costs and decrease the welfare in the short term, but it will increase the welfare in the long term.

The designed carbon-cap and ETS policy in all the scenarios of this chapter will help China meet the committed INDC target of the carbon intensity reduction but cannot help China meet the INDC target of peaking the emissions. This is because the emission reduction of the carbon-cap and ETS policy is set to equal that of the carbon tax, and the designed carbon tax cannot help China peak its emissions committed in the INDC target, according to the previous chapters.

Overall, the desired ETS policy, implied by this chapter, should have a higher allocation of the carbon quotas; a lower proportion of the free quotas for the given carbon quotas; allowing the trading of the carbon quotas. At a stricter target of the emission reduction, banning the trading of the free quotas will deteriorate the welfare in the short term but will improve the welfare in the long term.

Conclusion

Compared to the 2015 scheme, the 2005 scheme will induce fewer carbon quotas allocated among the sectors. Hence, under the 2005 scheme, the carbon price and emission costs will be higher, but the RGDP will be lower. As the targeted emission reduction increases, both the carbon price and emission costs will increase, but the RGDP loss, induced by the climate policy, will decrease. As the decline factor increases or the rate of the free quotas decreases, both the carbon price and emission costs will unexpectedly decrease; in the meantime, the RGDP and household welfare will increase by less than 2%.

At the target of the 1% tax, the carbon trading will decrease the carbon price and increase the household welfare, but its impacts on the emission costs and RGDP will be less significant. Banning the FCQ trading will have almost no impacts on the carbon price and emission costs as well as the RGDP and household welfare. In contrast, at the target of the 2% tax, the carbon trading will induce a sudden drop of the carbon price in 2024–2025 because the fine price will apply owing to the over-emissions. The carbon trading will decrease the emission costs and increase the welfare, whilst banning the FCQ trading will increase the emission costs and decrease the welfare in the short term. However, in a more sophisticated ETS market, banning the FCQ trading could decrease the emission costs, increase the RGDP by approximately 5%, decrease the household welfare loss by approximately 3%, and increase the household emissions in the long term.

The designed carbon-cap and ETS policy in all the scenarios will reduce the carbon intensity to the extent where the Chinese government committed in the INDC target.

Chapter 8: Overall Discussion

Main Findings

Chapter 1 shows that modelling the electricity carbon emissions from the electricity consumption perspective is beneficial to revealing the genuine household and sectoral emissions. Disaggregating the electricity sector is helpful to implement the carbon tax fairly. There are minimal differences in the policy effects between the Pigouvian and output tax; however, the output tax will generate much more tax revenues than that of the Pigouvian tax. There will be less than 0.1% differences in the policy effects of recycling the tax revenues; hence, recycling the revenues is not an important complementary policy of the carbon tax. The carbon tax has diminishing marginal effects on the carbon emissions, carbon intensity, tax revenues, household welfare, and RGDP loss.

Chapter 2 shows that the ancillary (health) benefit of the carbon tax will increase the household carbon emissions by 0.15%–0.4%. The health benefit will decrease the household welfare and real GDP loss by 0.2%–0.45% and 0.015%–0.055% respectively. Nevertheless, the health benefit has almost no impacts on the policy effects of recycling the tax revenues.

Chapter 3 shows that the primary benefit will increase the household emissions by 0.10%–0.17%, decrease the carbon intensity by approximately 0.01%, and decrease the household welfare loss by 0.1%–0.3%. The primary benefit will minimally increase the average social cost of carbon (ASCC) in the tax scenarios because it will increase the emissions.

Chapter 4 shows that the technical impacts of the carbon tax will increase the energy cost share (ECS), decrease the energy-use efficiency (EUE) and energy-production efficiency (EPE), and increase the nonenergy-production efficiency (ENE). The technical impacts will decrease the carbon intensity by 1%–4% and RGDP loss by 2%–3.8%. However, the technical impacts will minimally increase the household welfare loss, climate damages, abatement costs, and ASCC.

Chapter 5 shows that the inequality impacts of the carbon tax are related to the assumption of the distribution of the climate damages, payment of the abatement costs, and recipient of the tax revenues. The relative utility is mainly determined by the absolute income even though the income inequality does have an impact on it. The net utility is mainly determined by the total utility, whilst it is only minimally affected by the relative utility. Hence, the inequality impacts will minimally influence the policy effects of the carbon tax.

Chapter 6 shows that the urbanisation will decrease the household emissions by 0.2%–0.8% and carbon intensity by 2%–5% in 2015–2030. In the tax scenarios, the urbanisation will decrease the RGDP and household welfare. The urbanisation will increase the climate damages by 2%–5%, decrease the technical index by less than 0.25%, increase the Palma ratio by 3%–6.5%, and increase the average social cost of carbon (ASCC) by 2.5%–6%.

Chapter 7 shows that at the same abatement target, the carbon-cap or ETS policy will induce the higher household welfare and RGDP. Under the 2005 quota allocation scheme, the carbon price and emission costs will be higher, but the RGDP will be lower than the 2015 quota allocation scheme. As the targeted emission reduction increases, both the carbon price and emission costs will increase, but the RGDP loss, induced by the climate policy, will decrease. The decline factor will decrease the carbon price and emission costs, but it will increase the RGDP and household welfare. At the target of the 1% tax, the carbon trading will decrease the carbon price and increase the household welfare. Banning the FCQ trading will have almost no impacts on the effects of the ETS policy. In contrast, at the target of the 2% tax, the carbon trading will decrease the emission costs and increase the welfare, whilst banning the FCQ trading will increase the emission costs and decrease the welfare in the short term. However, in a more sophisticated ETS market, banning the FCQ trading could decrease the emission costs and increase the welfare in the long term.

The sensitivity analysis shows that the model results are robust to the income elasticities, the parameter of the unit change of the labour productivity to $PM_{2.5}$ pollution, and the geophysical parameters excluding the damage parameter. The relative utility is quite robust to the parametric values of γ_1 but quite sensitive to the parametric values of γ_2. Even if γ_2 may significantly change the relative utility, the variation of the relative utility is still very minimal compared to the total welfare.

Discussion

The carbon tax will decrease the carbon emissions significantly, but it will not distinctly affect the carbon intensity. The significant emission reduction effect of the tax is in line with Dong, Dai et al. (2017) who used a 30-Chinese-province CGE model to show that the carbon tax would decrease the Chinese industrial carbon emissions significantly. However, the indistinct policy effect on the intensity disagrees with Li, Dai et al. (2018) who showed that the tax could decrease the carbon intensity by over 20% and 25% in Liaoning Province and the rest of China respectively. The result difference lies in the structure of the CGE model: Li, Dai et al. (2018) modelled the provincial inflow and outflow of the consumption and production if the tax rate differed across the regions. In contrast, the carbon tax is imposed at the same rate across China in this paper. Also, there was a scale effect of the production and consumption in Liaoning Province compared to the rest of China in Li, Dai et al. (2018), whilst the economic scale of the RW is assumed to be not affected by the Chinese carbon tax in this paper.

The carbon tax will decrease the household welfare and real GDP (RGDP). The negative effect of the tax on the household can be also found in Guo, Zhang et al. (2014) who used a CGE model to investigate the socioeconomic impacts of the Chinese carbon tax. The negative effect on the RGDP complies with Dong, Dai et al. (2017) who used a 30-Chinese-province CGE model and concluded that the implementation of the carbon tax would impede the economic development for all the Chinese provinces.

The carbon tax has the diminishing marginal effects on the emission reduction and welfare loss. The diminishing effect on the emission reduction complies with Knobloch, Pollitt et al. (2019) who employed the non-equilibrium bottom-up model to empirically show that the carbon tax had a decreasing marginal impact on the total emission reduction. The diminishing marginal effect on the welfare can be also found in Xiao, Niu et al. (2015) who used a dynamic recursive multi-sectoral CGE model to study the impacts of the environmental tax in China.

The revenue recycling policy will have a minimal impact on the policy effects of the tax. This finding disagrees with Sands (2018) who used a CGE model to empirically show that the revenue recycling could make a difference to the policy effects of the carbon tax in the US. The result difference between Sands (2018) and this paper lies in the way the revenues are recycled: the revenues were recycled as the reduction in the labour or capital tax in Sands (2018). By comparison, in this paper, the tax revenues are recycled as the increase in the income of the targeted entity directly.

The ancillary (health) benefit of the carbon tax will decrease the carbon emissions and carbon intensity. The negative impact on the emissions agrees with Fox, Zuidema et al. (2019) who reviewed the literature on the public health's role in climate change action, arguing that the health benefit helped underpin the greenhouse gas reduction strategies. The negative impact on the intensity complies with Wang, Ye et al. (2014) who developed a multi-region optimisation model to show that the current local air pollution control targets contributed slightly to the decrease of the carbon intensity in the Chinese power sector.

The ancillary benefit will increase the household welfare. The positive impact on the household welfare can be also found in Jensen, Keogh-Brown et al. (2013) who employed a single-country dynamic recursive CGE model to assess the health co-benefits of the UK greenhouse gas emission reduction strategies. By comparison, the health benefit will have a much smaller and positive impact on the RGDP. This minimal health benefit impact could be explained by the mismatch between the sectors with the high potential for emission reductions and the sectors with the high health benefits per unit emission reduction (Liu, Huang et al. 2017).

The primary (climate) benefit will slightly reduce the carbon intensity. Similar findings can be found in Trotta (2020) and Buonocore, Luckow et al. (2016). By comparison, the primary benefit will significantly decrease the deadweight loss of the carbon tax, especially for the agriculture sector whose output is severely affected by the climate change. For example, Sathre and Gustavsson (2009) developed a bottom-up method to empirically show that the climate benefit of the carbon tax significantly increased the output of the forest product industries.

The primary benefit of the carbon tax will increase the climate damages because it will increase the emissions and thus exacerbate the climate change. This is because the primary benefit of the Chinese carbon tax could have a global impact but only the regional impact is modelled in this paper. A previous study on the US climate policy concluded that the US policy resulted in a net cooling on a global scale, but the policy led to a net positive forcing over the USA on a regional scale (Lee, Shindell et al. 2016). By comparison, the primary benefit will minimally affect the abatement costs, and the impact is positive in most cases. This is because in developing countries, primary benefits play a minor role on the political agenda (Rubbelke 2006). Nevertheless, climate benefits are more concerned in the developed countries. For example, Woollacott (2018) used the forward-looking dynamic CGE model to identify the required climate benefits to justify the emission abatement in the US.

The ITC will decrease the energy-use efficiency (EUE) and energy-production efficiency (EPE) in the tax scenarios. The negative impact of the ITC on the EUE disagrees with Kemfert and Truong (2007) who showed that the ITC improved the energy efficiency. The result difference between Kemfert and Truong (2007) and this paper lies in the socioeconomic conditions where the ITC impacts are analysed: Kemfert and Truong (2007) directly studied the ITC impacts caused by the increase of the R&D investment, whilst the ITC impacts are analysed under the carbon tax in this paper. The negative ITC impact on the EPE complies with Macaluso, Tuladhar et al. (2018) who provided a cross-model analysis to show that the carbon tax would induce the substitutions toward less carbon-intensive energy sources and production technologies in the US.

The ITC will increase the nonenergy-production efficiency (ENE). This finding complies with Ekins, Pollitt et al. (2012) who empirically found that the EU environmental tax reform could increase the material productivity by 3.4%. By comparison, the ITC will promote the technical progress at the lower tax rate. However, at the higher tax rate, the ITC inhibited the technical progress recently but will promote the progress in the future. The promotion impact of the ITC agrees with Jin (2012) who used an intertemporal CGE model to show that a climate policy could induce additional R&D investment and knowledge application in carbon-saving innovations in China. The inhibition impact of the ITC implies that owing to the socioeconomic constraints, the carbon pricing was ineffective to orientate the technical progress (Finon 2019).

The ITC will increase the RGDP but decrease the household welfare. The positive ITC impact on the RGDP can be also found in Kemfert (2005) who used the multiregional and multi-sectoral integrated assessment model to conclude that the ITC would support the carbon-free technologies and thus lead to an economic boom. The negative ITC impact on the household welfare could be explained by the uncertainties existing in the household decision-making (Knobloch, Pollitt et al. 2019).

The income elasticity of damage (ξ) affects the inequality condition. The climate change would exacerbate the inequality condition, according to Beck (2010) who remapped the social inequality at the age of the climate change. If the abatement costs of the carbon tax are independent from the income, the tax will increase the inequality condition. This finding complies with Markkanen and Anger-Kraavi (2019) who showed that a carbon tax would usually increase the inequality condition because of the rising energy prices.

A decrease in the income, caused by the increase of the tax rate, will induce an increase in the absolute value of the relative utility. This finding complies with Clark, Frijters et al. (2008) who reviewed the evidence on the relative income from the well-being literature, arguing for the positive correlations between the individual income and well-being irrespective of the negative relation between the happiness and others' income.

Recycling the tax revenues to the household will induce the lowest inequality condition in comparison with the recycling policies to the other recipients. This finding is compatible with Montenegro, Lekavicius et al. (2019) who used a multi-regional CGE to show that redistributing the revenues from the carbon certificates decreased the income inequality in EU, as the poor derived a higher share of their income from the governmental income redistribution than the rich. Recycling the revenues to the low-income household subgroup only will induce the most equitable condition. A similar finding can be found in Jorgenson, Goettle et al. (2018) who employed an intertemporal CGE model to study the welfare consequences of the carbon taxation.

The urbanisation will decrease the carbon emissions and intensity in China. This finding is contrary to Wang, Wu et al. (2016) who argued that the urbanisation increased the carbon emissions in China. The result difference between Wang, Wu et al. (2016) and this paper is caused by the choices of the explanatory variables: Wang, Wu et al. (2016) omitted the correlation between the urbanisation and GDP, whilst this paper has fully explored the interrelations among the GDP, emissions, energy consumption, and urbanisation.

In the tax scenarios, the urbanisation will decrease the household welfare and RGDP. The negative urbanisation impact on the household welfare complies with Van de Poel, O'Donnell et al. (2012) who empirically showed that the urbanisation might lead to the unhealth lifestyles. The negative impact of the urbanisation on the RGDP complies with Liddle (2013) who adopted a panel method to show that the urbanisation had a "ladder" impact on the income: it had a strong negative impact on the poorest countries, a less negative to neutral impact on the countries with the moderate incomes, and a reinforcing impact on the wealthy countries. As the carbon tax will decrease the national income, the urbanisation impact on the economic growth could become negative under the carbon tax.

The urbanisation will pose an adverse impact on the technical progress. This finding is contrary to Duman and Kasman (2017) who empirically showed that the urbanisation improved the environmental technical efficiency in the EU. The result difference between Duman and Kasman (2017) and this paper lies in the targeted scope of the induced technological change: Duman and Kasman (2017) only researched the environmentally friendly technologies, whilst the technical index considers all kinds of the tax-induced technologies in this paper.

The carbon trading will decrease the carbon price at the target of the 1% tax and in 2025–2030 at the target of the 2% tax. This finding agrees with Wu, Dai et al. (2019) who utilised a CGE model to conclude that the shadow prices of most sectors in the cap-without-trade scenarios were higher than the actual carbon price in Taiwan. The carbon price is not linearly correlated with the emission costs, but the costs are influenced by the allocation scheme of the carbon quotas. The more quotas are given to a sector, the less emission costs the sector will have. This finding complies with Wu, Dai et al. (2016) who concluded that the average costs would almost double in 2020–2030 in Shanghai, owing to the increasingly stricter carbon cap.

The emission costs will be reduced by the decline factor of the free quotas. Conversely, Lin and Jia (2018) used a dynamic recursive CGE model to show that a higher decline factor would increase the emission costs. The policy coverage may explain this result difference. Only a few sectors were covered in Lin and Jia (2018) who did not consider and calculate the future carbon emissions of the noncovered sectors. By comparison, in this paper, almost all the sectors are covered by the carbon-cap policy except for the electricity subsectors exploiting renewables only.

The decline factor of the free quotas will increase the RGDP. This finding disagrees with Wu and Li (2020) who used a dynamic recursive CGE model to show that the higher the free allocation ratio was, the greater the GDP would be in China. The result difference between Wu and Li (2020) and this paper lies in the assumption of the projected GDP growth rate: the GDP growth rate was endogenously determined and also affected by the decline factor in Wu and Li (2020), whilst the real GDP in this paper is assumed to grow at the given rate by OECD (2018). The carbon trading will also increase the RGDP. This finding complies with Wang, Dai et al. (2015) who used a two-region dynamic CGE model to empirically show that the ETS policy could reduce the mitigation costs and thus increase the GDP.

The decline factor of the free quotas will increase the household welfare. This finding disagrees with Lin and Jia (2018) and Zhang, Li et al. (2018) who argued that the higher decline factor would decrease the household welfare. This result difference mainly lies in the assumption on the ETS revenues: the government transferred the ETS revenues to the household in Lin and Jia (2018) and Zhang, Li et al. (2018). In contrast, the ETS revenue recycling is not considered in this paper, because the revenues of the 10% non-free quotas are small compared to the macroeconomic variables. The carbon trading will increase the household welfare. This finding is in line with Wu, Dai et al. (2019) who used a CGE model to show that the consumption loss, caused by the carbon-cap policy, diminished under the ETS policy, and the reduction of the consumption loss would increase the household welfare in Taiwan.

In summary, the empirical results in this paper generally fit in well with the literature except that the result differences are mainly caused by the model assumptions and research methods.

Limitations and Future Research

The designed revenue recycling policy could be one limitation in this paper, because the revenues are given to an entity as an increase of its income. In the reality, the tax revenues can be used to stimulate the economic growth, like the refund of the capital tax and labour tax. Future research may lie in the detailed study of the mechanism that the revenue recycling complements the policy effects of the carbon tax.

To model the ancillary benefit, I have assumed that the labour productivity is linearly correlated with the $PM_{2.5}$ concentrations. However, this linear relation may not exist in the reality. For example, Chang, Zivin et al. (2016) empirically found that an increase in the $PM_{2.5}$ concentrations led to the significant decreases in the productivity of the pear packers with the impacts arising at the levels below the air quality standards. Hence, future research may comprehensively model the relation between the labour productivity and air pollution.

The labour productivity is also influenced by other air pollutants, such as SO_2, NO_x, and PM_{10}, in addition to $PM_{2.5}$. A climate policy that curbs the carbon emissions may also reduce the emissions of these air pollutants, and thus the health benefit in the reality can be much larger than the benefit this paper has estimated. Therefore, a composite index, denoting the concentrations of all kinds of the air pollutants, may be conducive to revealing how the air pollutants will reduce the labour productivity more clearly.

The improved labour health is beneficial to the human capital accumulation as the capital damages are assumed to be linear to the level of the air pollution (Bretschger and Karydas 2018). The clean air can also improve the labour health by encouraging the active transportation choices, improving the ecosystems, and promoting the health equity in the society (Ambasta and Buonocore 2018). Hence, future research may comprehensively explore the other aspects of the health benefit. More importantly, as health benefits are only part of ancillary benefits, an unbiased study may fully explore all kinds of the ancillary benefits of a climate policy.

The damage parameter will place undue influences on the climate damages. Future research may lie in a clear clarification of the damage function, whose result should be insensitive to the exogenous values of the damage parameter. In addition, the measurement of the household welfare is sensitive to the variation of the inequality parameter. Hence, the quantification of the household welfare also needs to be improved in a way that its value should not be susceptible to the given value of the inequality parameter.

In this paper, I have only modelled the regional primary benefit of the Chinese carbon tax, and thus I may underestimate the entire primary benefits of the tax. This is because the climate benefits usually extend beyond the local region where the climate policy is implemented (Lee, Shindell et al. 2016). Future research may lie in the modelling of the global primary benefits of the Chinese carbon tax.

I have only modelled the induced technological change (ITC) of the carbon tax, but the model cannot reveal the pure socioeconomic impacts of the technical progress. The ITC is quantified basing on Wang, Saunders et al. (2019) who argued that the ITC mainly included the potential changes of the energy-saving technologies but excluded the induced development of the decarbonisation or clean energies. The narrowed scope of the ITC may underestimate the technical impacts. Future work may improve the quantification method of the ITC to include all types of the potential technological changes under the carbon tax.

The relative utility (RU) is insensitive to the parametric value of the weight of relative income (γ_1) but quite sensitive to the rate at which the RU falls as the income rises (γ_2). Future research may improve the definition of the RU so that its value is robust to the given values of both γ_1 and γ_2.

The urbanisation is assumed to exogenously influence the policy effects of the carbon tax. The exogenous determination may induce a biased evaluation of the urbanisation impacts: the optimal policy is based on the given inputted parameters describing the urbanisation impacts, but these parameters should vary freely to form the optimal policy. Hence, future research may lie in the use of detailed urban-rural population dispersion data to endogenously model the urbanisation impacts in the CGE policy evaluation framework.

To achieve the same abatement target as the carbon tax, the ETS policy will induce a high carbon price. However, the carbon price of the ETS market may not reach the simulated level in the reality, because the exorbitant price may induce some covered sectors to be overwhelmed (Lin and Jia 2017). To overcome the overwhelming carbon pricing under the ETS policy, a potential complementary study lies in analysing the ETS impacts on the emission reduction assuming the equal welfare impacts. In the complementary study, the ETS carbon pricing is directly linked to the welfare effects of the carbon tax. As the carbon tax may not severely harm the economic output, the ETS carbon pricing could be reasonable. Perhaps, this paper and the potential complementary study altogether may comprehensively reveal whether the carbon tax or ETS policy is preferable.

Policy Implications

The carbon tax should be imposed on the electricity consumption rather than electricity generation. A differentiated carbon tax on the electricity subsectors is better than a uniformed tax on the electricity sector. Compared to the Pigouvian tax, the output tax is more advantageous to be implemented as a second-best climate policy because of much more tax revenues generated. Recycling the tax revenues is not an important complementary policy of the carbon tax; however, it affects the inequality conditions. The carbon tax has diminishing marginal effects both on the emission reduction and welfare loss; however, the marginal effects are almost not affected by the ancillary (health) benefit.

The health benefit will weaken the policy effects of the carbon tax on the emission reduction and welfare loss. In contrast, the primary benefit will weaken the policy effects of the carbon tax on the emission reduction, but it will strengthen the policy effects on the intensity reduction and welfare loss.

The technical impacts will strengthen the policy effects of the tax on the emission reduction, but it will weaken the negative effects of the tax on the welfare. However, the inequality impact is not a significant factor that influences the policy effects of the carbon tax. By comparison, the urbanisation will strengthen the policy effects of the carbon tax on the emission reduction and welfare loss.

Hence, when the Chinese government designs the carbon tax, it should fully consider the influences of the ancillary benefit, primary benefit, technical impacts, inequality impacts, and urbanisation impacts on the policy effects of the tax.

Although carbon taxes are popular in China, the government should support more on ETS policies. This is because at the same abatement target, the ETS policy will induce the higher welfare than that of the carbon tax. The desired ETS policy includes a higher allocation of the carbon quotas; a lower proportion of the free quotas for the given carbon quotas; allowing the trading of the carbon quotas. At a stricter abatement target, banning the trading of the free quotas will deteriorate the welfare in the short term but will improve the welfare in the long term.

Considering all the influential factors, China will still meet the INDC target of the carbon intensity reduction under the designed carbon tax and ETS policy. Nevertheless, the carbon tax and ETS policy cannot help China meet the INDC target of peaking the emissions. To meet this INDC target, China needs to implement more climate policies or researchers need to consider more influential factors in the policy evaluation framework.

Overall, I have established a research framework where climate policies can be evaluated less biasedly, compared to most previous studies. The research framework can provide theoretical and practical guidance to the Chinese government when designing climate policies. In addition, the research framework can be applied to analyse the effects of climate policies elsewhere, considering the accelerating global warming faced by the human beings.

Appendix A: Tables and Figures

Tables

Table A1.1 The Sector Division of the Chinese Economy

1.Agriculture, Forestry, Animal Husbandry & Fishery	1.Agriculture (agric)
2.Mining and Washing of Coal	2. Mining and Washing of Coal (coalm)
3.Extraction of Petroleum and Natural Gas	3.Extraction of Petroleum (petrm) 4.Extraction of Natural Gas (gasn)
4.Ferrous Metal and Ore Mining 5.Non-metal Minerals and Other Mining	5. Metal, Ore, Non-metal and Other Mining (othm)
6.Foods and Tobaccos	6. Foods, Beverage & Tobacco (food)
7.Textile Products 8.Textile Wearing Apparel, Footwear and Caps, Leather, furs, down and related products	7.Textile Related Products (texti)
9.Processing and Manufacture of Timber and Furniture 10. Paper and Printing, Cultural, Sporting and Athletic and Recreation Products	8. Timber Related Products and Recreational Products (furni)
11. Petroleum Processing, Coking, and Nuclear Fuel Processing	9. Petroleum, Nuclear Fuel Processing (petrp) 10.Coking Processing (coking)
12. Chemical Product	11. Chemical Industry (chemical)
13. Manufacture of Non-metallic Mineral Products	12. Non-metallic Mineral Products (mineral)
14. Smelting and Pressing of Ferrous Metals	13. Metal Products (metal)
15. Metal products	
16. Manufacture of General-Purpose Machinery 17. Manufacture of Special Purpose Machinery 18. Manufacture of Railroad Transport Equipment 19. Manufacture of Electrical Machinery and Equipment 20. Manufacture of Communication Equipment, Computers and Other Electronic Equipment 21. Instruments, meters and other measuring equipment 22. Other Manufacturing Products 23. Scrap and Waste 24. Metal products, Machinery and Equipment Maintenance Service	14. Machinery and Equipment (machi)
25. Production and Distribution of Electric Power and Heat Power	15. Electricity Production and Distribution (ED) 16. Heat Production and Distribution (fipow)
26. Production and Distribution of Gas	17. Gas Production and Distribution (gasm)
27. Production and Distribution of Water	18. Water Production and Distribution (water)
28. Construction	19. Construction (const)
29. Wholesale and Retail Trade	21. Other Service (service)
30. Transport, Storage and Post	20. Transport, Storage and Post (trans)
31. Hotels and Restaurants 32. Information Transfer, Computer Services and Software 33. Finance 34. Real Estate 35. Tenancy and Business Services 36. Scientific Research and Technical Service 37. Management of Water Conservancy, Environment and Public Establishment 38. Resident Services, Maintenance Service and Other Services 39. Education 40. Sanitation and Social Work 41. Culture, Sports and Entertainment	21. Other Service (service)

42. Public Management Social Security & Social Organisations	

Table A1.2 The Default Elasticity Parameters in This Chapter

	rhoQX	rhoKEL	rhoKE	rhoE	rhoCPG	rhoPG	rhocoal	rhogas	rhopetr	rhopow	rhoQq	rhoCET
agric	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	3	4
othm	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
food	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
texti	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
furni	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
chemical	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
mineral	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
metal	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
machi	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
commu	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
const	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2	3
trans	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2	3
service	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2	2.5
coalm	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2	2.5
coking	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
petrm	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
petrp	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
gasn	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
gasm	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	2.5	3.5
fipow	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
TD	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
Supercrit	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
USC	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
subc	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
NG	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
Nuclear	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
Hydro	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
wind	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5
solarpv	0.3	0.8	0.6	1.2	1.2	1.3	1.25	1.6	1.25	3	1.1	0.5

Table A1.3 The Decomposition of the Electricity Sector

Electricity Production and Distribution (ED)	Electricity Transmission and Distribution (TD) Supercritical Coal Generation (Supercrit) Ultra-Supercritical Coal Generation (USC) Sub-c Coal Generation (Subc) Natural Gas Generation (NG) Nuclear Power Generation (Nuclear) Hydro Power Generation (Hydro) Wind Power Generation (Wind) Solar Power Generation (Solar)

Table A5.1 The Palma Ratio in SCRO5

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.53	2.55	2.56	2.53	2.54	2.55	2.52	2.53	2.55
2020	2.51	2.55	2.58	2.50	2.54	2.57	2.50	2.53	2.56	2.49	2.53	2.56
2025	2.52	2.58	2.63	2.51	2.57	2.62	2.50	2.56	2.61	2.50	2.55	2.61
2030	2.55	2.63	2.71	2.54	2.62	2.70	2.53	2.61	2.69	2.53	2.61	2.68

Table A5.2 The Palma Ratio in SCRO6

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.82	2.84	2.85	3.32	3.34	3.36	3.86	3.89	3.91
2020	2.51	2.55	2.58	2.73	2.77	2.81	3.07	3.12	3.17	3.38	3.44	3.50
2025	2.52	2.58	2.63	2.61	2.68	2.73	2.78	2.85	2.92	2.93	3.01	3.09
2030	2.55	2.63	2.71	2.58	2.67	2.75	2.67	2.75	2.84	2.75	2.84	2.93

Table A5.3 The Palma Ratio in SCRO8

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.52	2.54	2.55	2.51	2.52	2.53	2.49	2.50	2.52
2020	2.51	2.55	2.58	2.49	2.53	2.56	2.48	2.51	2.55	2.47	2.50	2.53
2025	2.52	2.58	2.63	2.50	2.56	2.61	2.49	2.54	2.60	2.48	2.53	2.59
2030	2.55	2.63	2.71	2.53	2.61	2.69	2.52	2.60	2.67	2.51	2.59	2.66

Table A5.4 The Palma Ratio in SCRO9

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.81	2.83	2.84	3.29	3.31	3.33	3.80	3.82	3.85
2020	2.51	2.55	2.58	2.72	2.76	2.80	3.04	3.09	3.14	3.34	3.40	3.46
2025	2.52	2.58	2.63	2.61	2.67	2.73	2.76	2.83	2.90	2.91	2.98	3.06
2030	2.55	2.63	2.71	2.58	2.66	2.74	2.65	2.74	2.82	2.72	2.81	2.90

Table A5.5 The Palma Ratio in SCRO11

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.54	2.55	2.56	2.54	2.55	2.56	2.54	2.55	2.56
2020	2.51	2.55	2.58	2.51	2.54	2.58	2.51	2.54	2.57	2.51	2.54	2.57
2025	2.52	2.58	2.63	2.51	2.57	2.62	2.51	2.57	2.62	2.51	2.57	2.62
2030	2.55	2.63	2.71	2.54	2.62	2.70	2.54	2.62	2.70	2.54	2.62	2.69

Table A5.6 The Palma Ratio in SCRO12

Tax	0%			1%			2%			3%		
ξ	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega	Posi	Zero	Nega
2015	2.55	2.56	2.57	2.83	2.85	2.86	3.34	3.36	3.38	3.89	3.92	3.95
2020	2.51	2.55	2.58	2.73	2.78	2.81	3.08	3.13	3.18	3.40	3.47	3.53
2025	2.52	2.58	2.63	2.62	2.68	2.74	2.79	2.86	2.93	2.95	3.03	3.10
2030	2.55	2.63	2.71	2.59	2.67	2.75	2.67	2.76	2.85	2.76	2.85	2.94

Table A5.7 The RU Change in the Baseline Scenario When ξ Is Negative

$\Delta\gamma_1$ or $\Delta\gamma_2$	-50%	-40%	-30%	-20%	-10%
ΔRU by $\Delta\gamma_1$	1.77%	1.40%	1.04%	0.68%	0.34%
ΔRU by $\Delta\gamma_2$	UND	25834.80%	2046.02%	526.37%	135.57%
$\Delta\gamma_1$ or $\Delta\gamma_2$	10%	20%	30%	40%	50%
ΔRU by $\Delta\gamma_1$	-0.33%	-0.65%	-0.96%	-1.26%	-1.56%
ΔRU by $\Delta\gamma_2$	-54.26%	-77.96%	-88.96%	-94.29%	-96.98%

Note: UND means undefined

Table A5.8 The RU Change in the 1% Tax Scenario When Tax Revenues Detained by the Government under the Abatement Costs Only to High-income Subgroup and ξ Is Negative

$\Delta\gamma_1$ or $\Delta\gamma_2$	-50%	-40%	-30%	-20%	-10%
ΔRU by $\Delta\gamma_1$	8.05%	6.37%	4.73%	3.12%	1.54%
ΔRU by $\Delta\gamma_2$	UND	21283.41%	1756.88%	468.74%	124.46%
$\Delta\gamma_1$ or $\Delta\gamma_2$	10%	20%	30%	40%	50%
ΔRU by $\Delta\gamma_1$	-1.51%	-2.98%	-4.43%	-5.84%	-7.22%
ΔRU by $\Delta\gamma_2$	-51.99%	-75.71%	-87.22%	-93.06%	-96.14%

Table A5.9 The RU Change in the 1% Tax Scenario When Tax Revenues Detained by the Government under the Abatement Costs Proportionally to the Income and ξ Is Negative

$\Delta\gamma_1$ or $\Delta\gamma_2$	-50%	-40%	-30%	-20%	-10%
ΔRU by $\Delta\gamma_1$	8.09%	6.40%	4.75%	3.13%	1.55%
ΔRU by $\Delta\gamma_2$	UND	20984.77%	1736.10%	464.26%	123.53%
$\Delta\gamma_1$ or $\Delta\gamma_2$	10%	20%	30%	40%	50%
ΔRU by $\Delta\gamma_1$	-1.51%	-3.00%	-4.44%	-5.86%	-7.25%
ΔRU by $\Delta\gamma_2$	-51.78%	-75.49%	-87.04%	-92.93%	-96.05%

Table A5.10 The RU Change in the 1% Tax Scenario When Tax Revenues Recycled to the Low-income Household under the Abatement Costs Proportionally to the Income and ξ Is Negative

$\Delta\gamma_1$ or $\Delta\gamma_2$	-50%	-40%	-30%	-20%	-10%
ΔRU by $\Delta\gamma_1$	8.08%	6.39%	4.74%	3.13%	1.55%
ΔRU by $\Delta\gamma_2$	UND	21029.39%	1739.32%	464.97%	123.68%
$\Delta\gamma_1$ or $\Delta\gamma_2$	10%	20%	30%	40%	50%
ΔRU by $\Delta\gamma_1$	-1.51%	-2.99%	-4.44%	-5.86%	-7.24%
ΔRU by $\Delta\gamma_2$	-51.81%	-75.53%	-87.07%	-92.96%	-96.07%

Table A6.1 The Results of the Unit Root Tests

Variable	Form	Intercept	Trend	Test	P-value	Unit Root
E_t	level	no	no	ADF	0.9799	yes
	level	no	no	PP	1.0000	yes
	1st DIFF	yes	no	ADF	0.1398	yes
	1st DIFF	yes	no	PP	0.0496**	no
	2nd DIFF	no	no	ADF	<0.0001**	no
	2nd DIFF	no	no	PP	<0.0001**	no
EC_t	level	no	no	ADF	0.9919	yes
	level	no	no	PP	1.0000	yes
	1st DIFF	yes	no	ADF	0.0868	yes
	1st DIFF	yes	no	PP	0.0694	yes
	2nd DIFF	no	no	ADF	<0.0001**	no
	2nd DIFF	no	no	PP	<0.0001**	no
GDP_t	level	yes	yes	ADF	0.0043**	no
	level	no	no	PP	1.0000	yes
	1st DIFF	yes	no	ADF	0.0020**	no
	1st DIFF	yes	no	PP	0.0179**	no
UR_t	level	no	no	ADF	0.9382	yes
	level	yes	no	PP	0.3091	yes
	1st DIFF	no	no	ADF	0.0996	yes
	1st DIFF	no	no	PP	0.1137	yes
	2nd DIFF	no	no	ADF	<0.0001**	no
	2nd DIFF	no	no	PP	<0.0001**	no

Note：** denotes statistical significance at the 5% level

Table A6.2 The P-values of the White and Breusch-Godfrey LM Tests

Test	$\Delta^2 E_t$	$\Delta^2 EC_t$	ΔGDP_t
White	0.8423	0.9971	0.4102
Breusch-Godfrey LM	0.2377	0.7495	0.0803

Table A6.3 The VIF Scores of the ARDL Models

Dependent	Independent	Uncentered VIF
$\Delta^2 E_t$	$\Delta^2 E_{t-1}$	2.1935
	$\Delta^2 EC_t$	1.5042
	$\Delta^2 EC_{t-1}$	1.4716
	ΔGDP_t	1.8013
	$\Delta^2 UR_t$	1.5188
$\Delta^2 EC_t$	$\Delta^2 EC_{t-1}$	1.9360
	$\Delta^2 E_t$	2.2258
	$\Delta^2 E_{t-1}$	2.7091
	ΔGDP_t	2.2458
	$\Delta^2 UR_t$	1.8326
ΔGDP_t	ΔGDP_{t-1}	37.5551
	ΔGDP_{t-2}	46.8721
	ΔE_t	44.5444
	ΔEC_t	52.9756
	ΔUR_t	37.0162

Table A7.1 The Corresponding Relations between Household Energy and Commodity Consumption

Energy	Commodity	Energy	Commodity
Coal	Coal	Supercrit-coal Electricity	Supercrit-coal Electricity
Charcoal	Coal	USC-coal Electricity	USC-coal Electricity
Crude Oil	/	Subc-coal Electricity	Subc-coal Electricity
Kerosene	Processed Petrol	Natural-gas Electricity	Natural-gas Electricity
Gasoline	Processed Petrol	Nuclear Electricity	Nuclear Electricity
Diesel Oil	Processed Petrol	Hydro Electricity	Hydro Electricity
Fuel Oil	/	Wind Electricity	Wind Electricity
Natural Gas	Gas and Natural Gas	Solar Electricity	/
Electricity Transmission and Distribution	Electricity Transmission and Distribution		

Figures

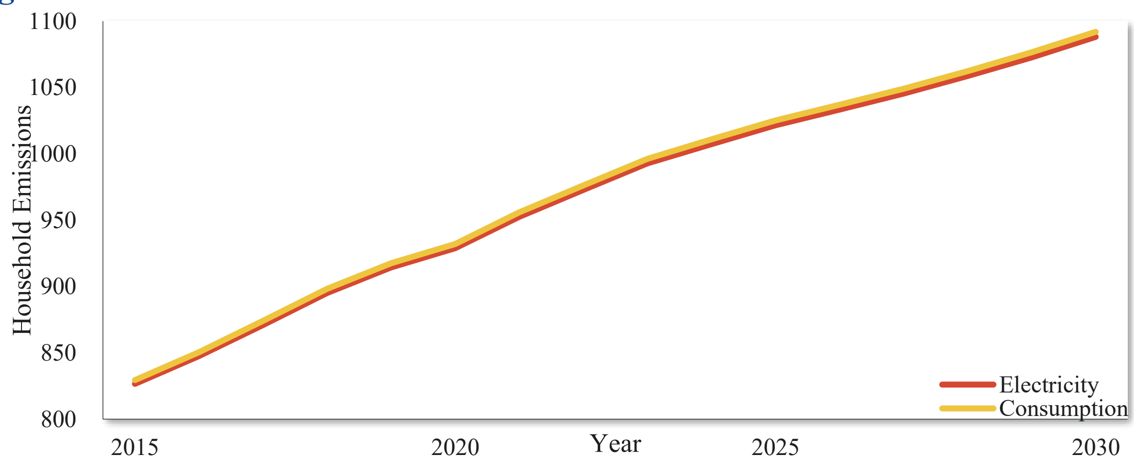


Fig. A1.1 The Baseline Household Emissions in the Consumption and Electricity Model (Unit: 10^6 t)

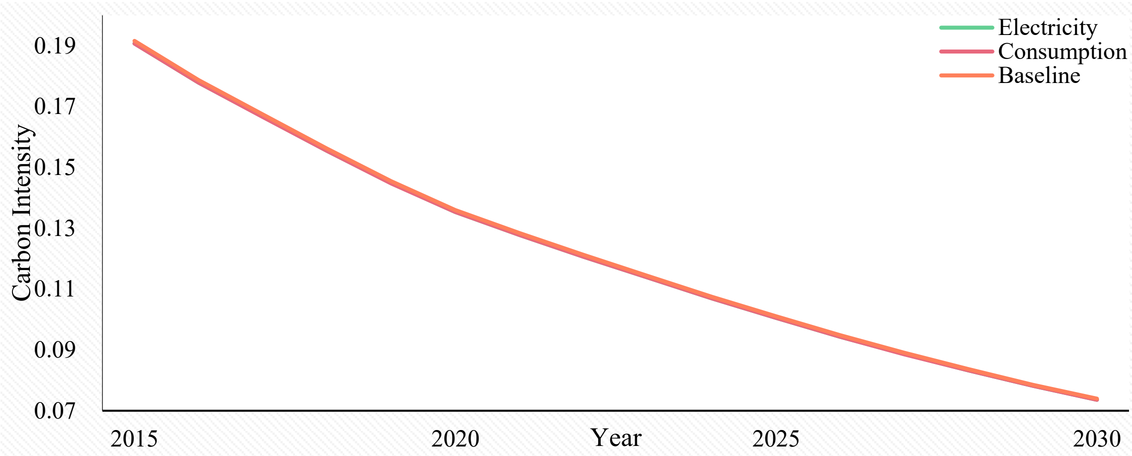


Fig. A1.2 The Carbon Intensity in the Consumption and Electricity Model (Unit: kg/ CNY)

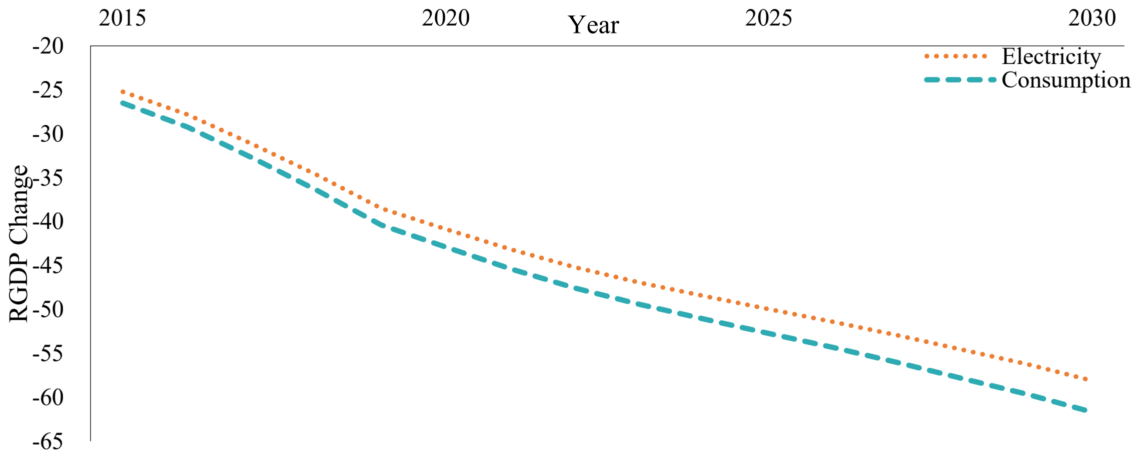


Fig. A1.3 The RGDP Change in the Consumption and Electricity Model (Unit: 10^{12} CNY)

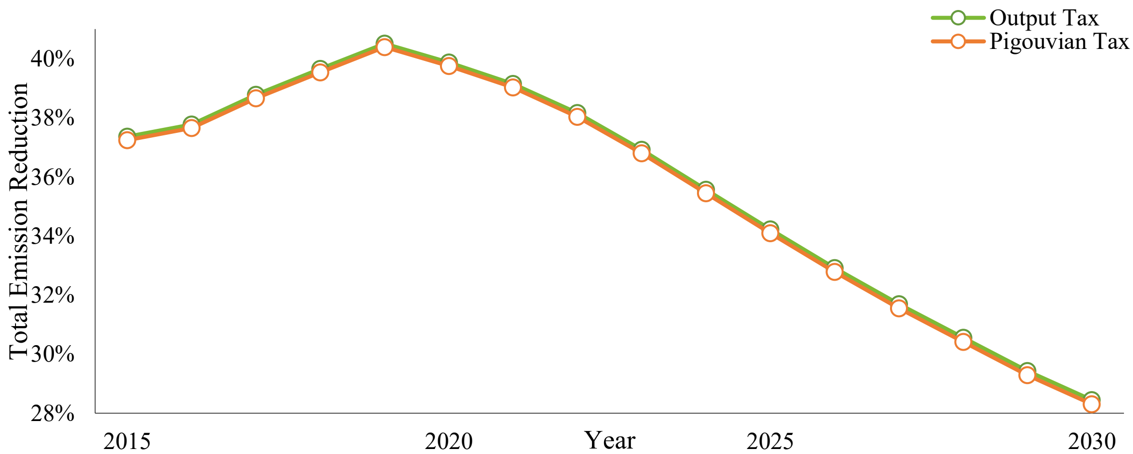


Fig. A1.4 The Total Emission Reduction under the Output and Pigouvian Tax

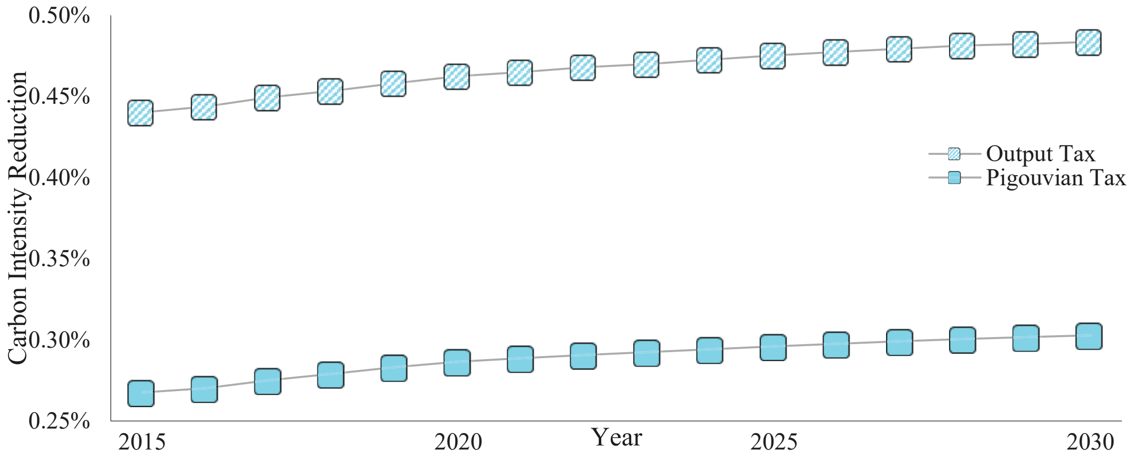


Fig. A1.5 The Carbon Intensity Reduction under the Output and Pigouvian Tax

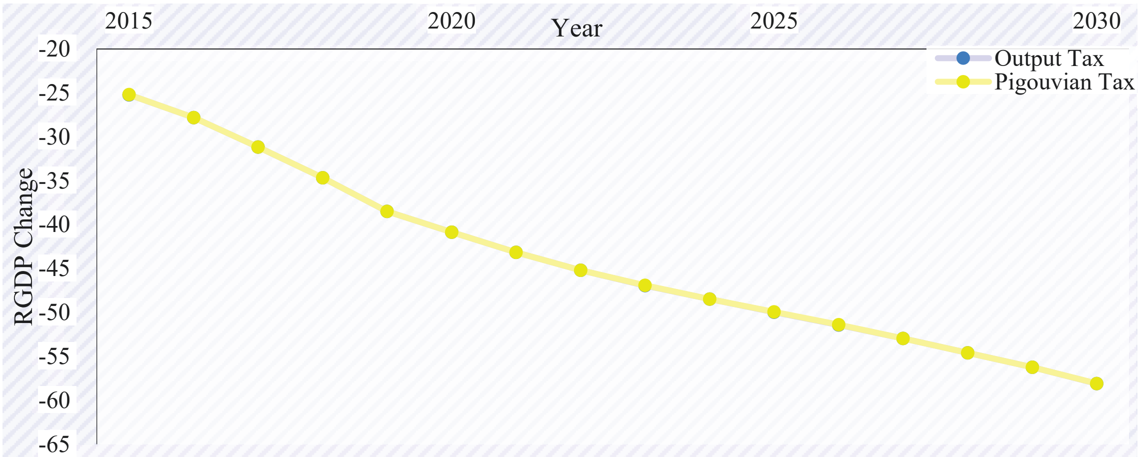


Fig. A1.6 The RGDP Change under the Output and Pigouvian Tax (Unit: 10^{12} CNY)

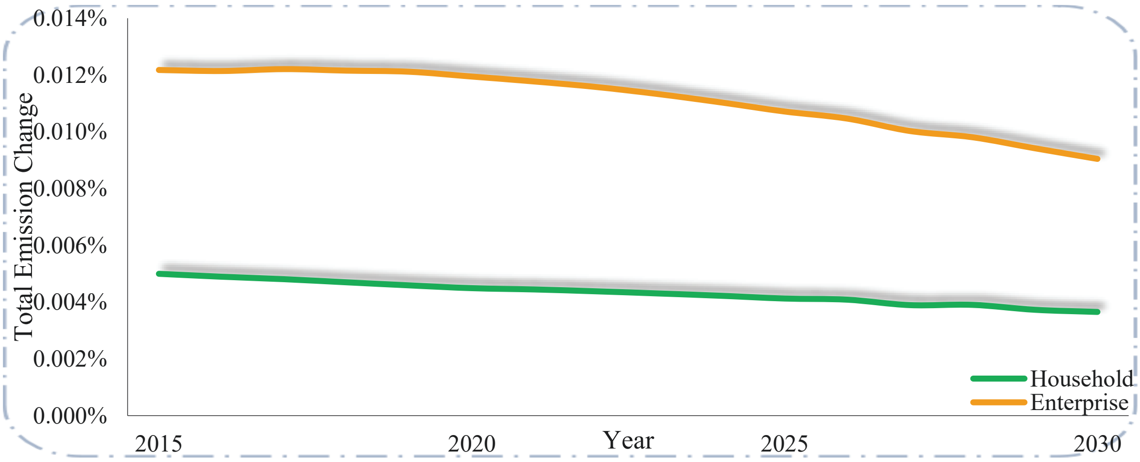


Fig. A1.7 The Total Emission Change under Recycling the Tax Revenues

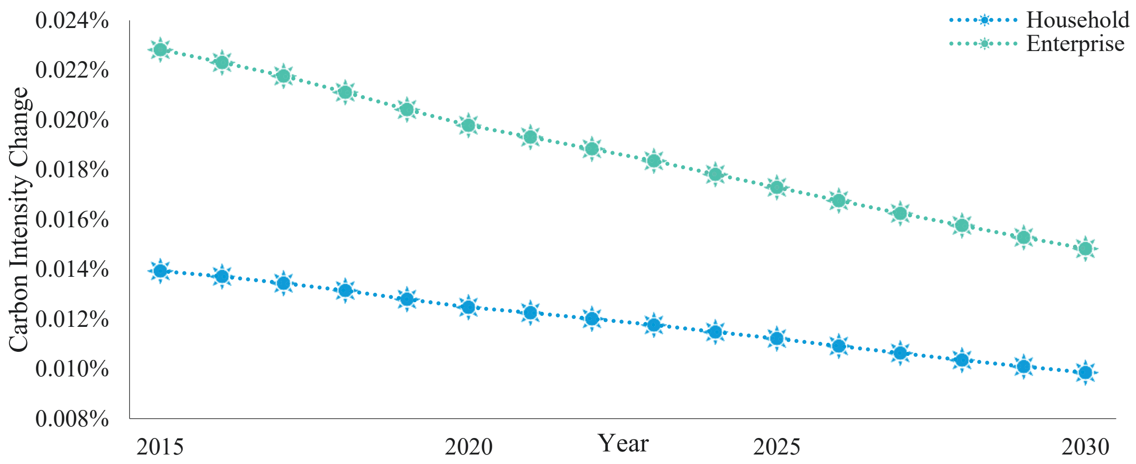


Fig. A1.8 The Carbon Intensity Change under Recycling the Tax Revenues

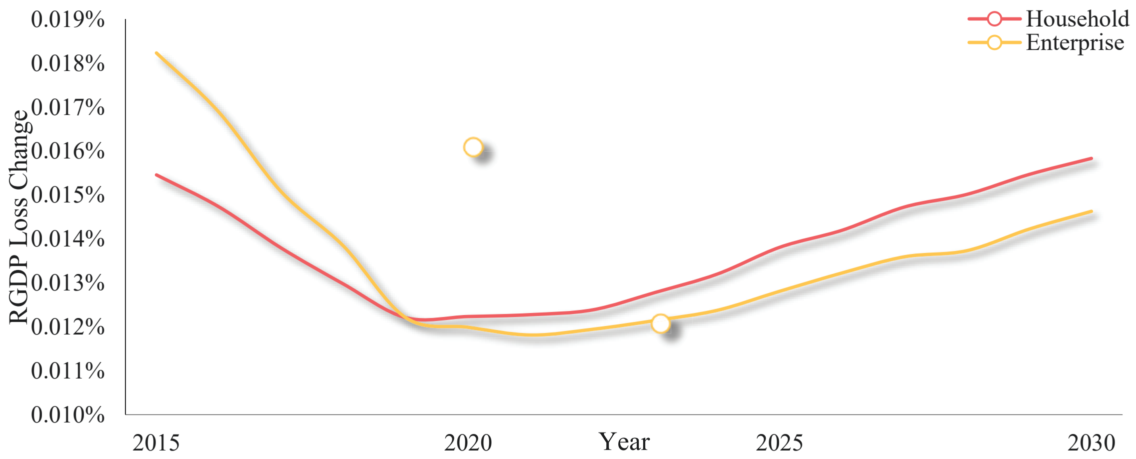


Fig. A1.9 The Change of the RGDP Loss under Recycling the Tax Revenues

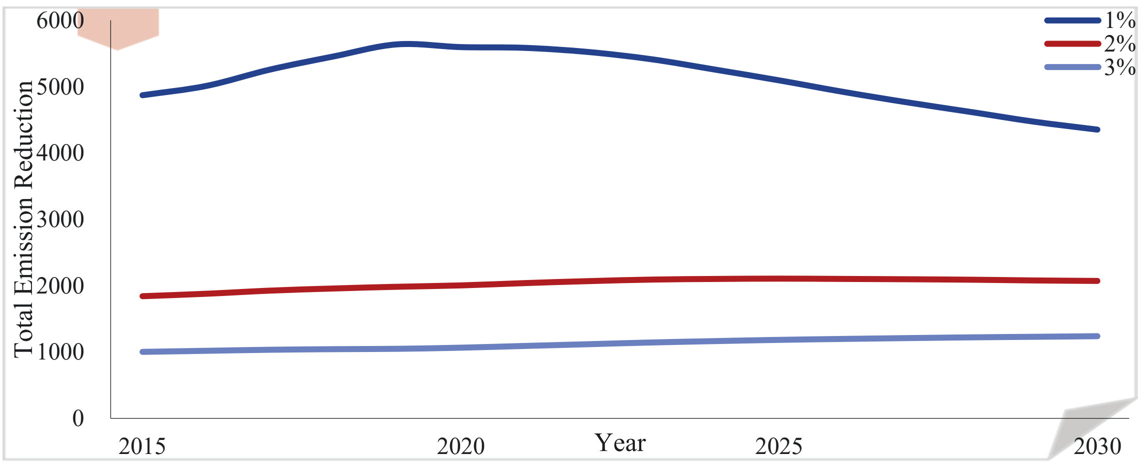


Fig. A1.10 The Marginal Policy Effect on the Total Emission Reduction (Unit: 10^6 t)

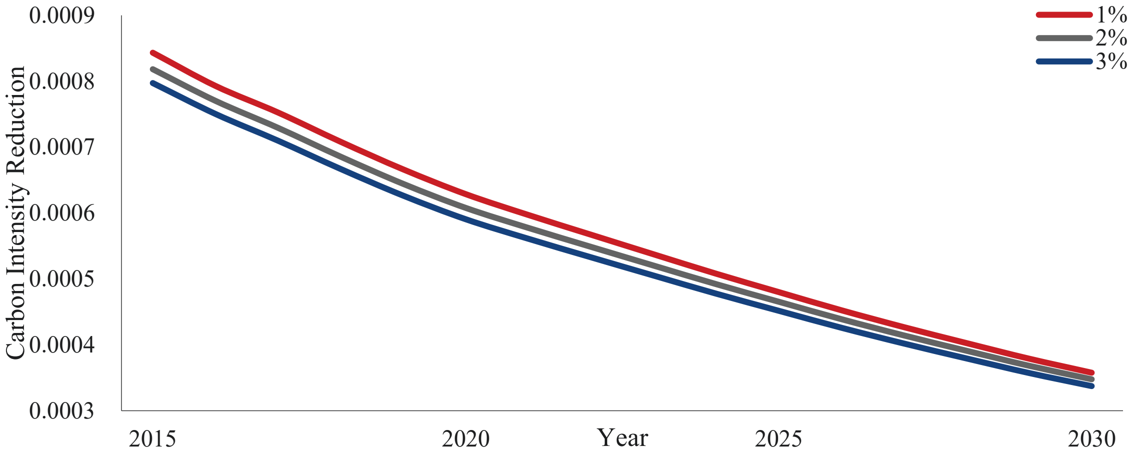


Fig. A1.11 The Marginal Policy Effect on the Carbon Intensity Reduction (Unit: kg/ CNY)

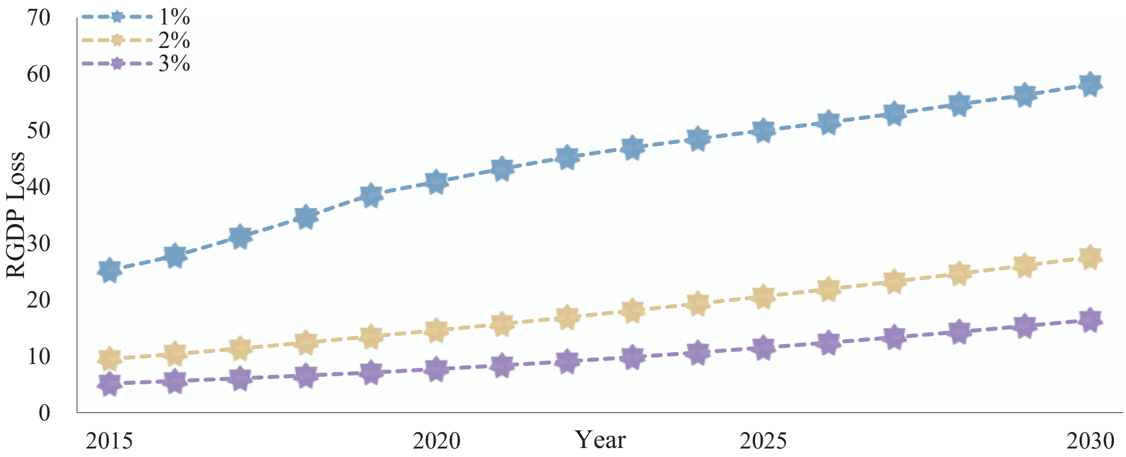


Fig. A1.12 The Marginal Policy Effect on the RGDP Loss (Unit: 10^{12} CNY)

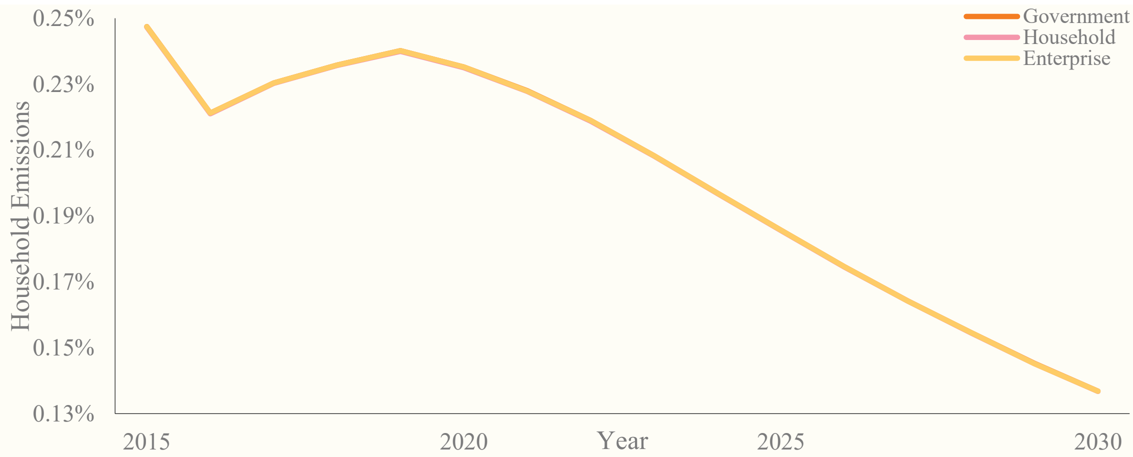


Fig. A2.1 The Health Benefit Impact on the Household Emissions under the Revenue Recycling

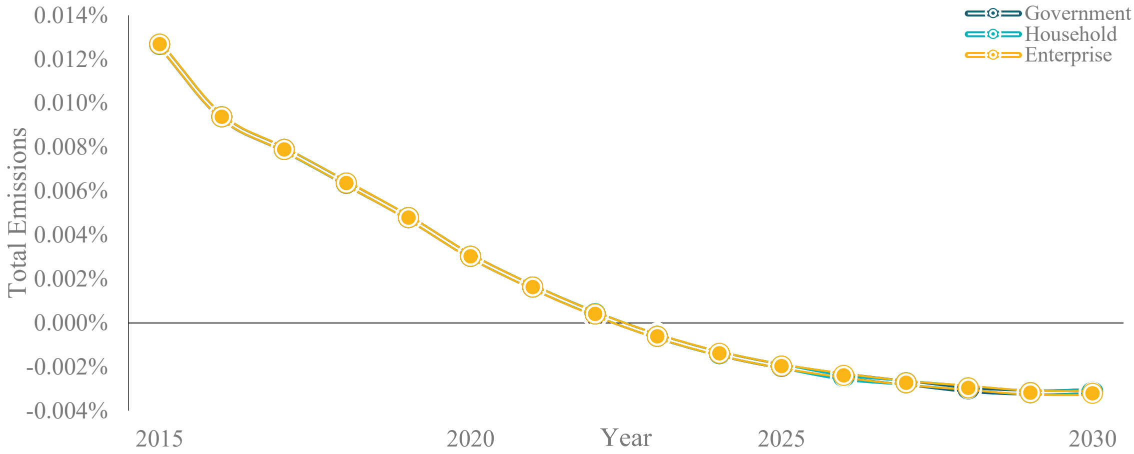


Fig. A2.2 The Health Benefit Impact on the Total Emissions under the Revenue Recycling

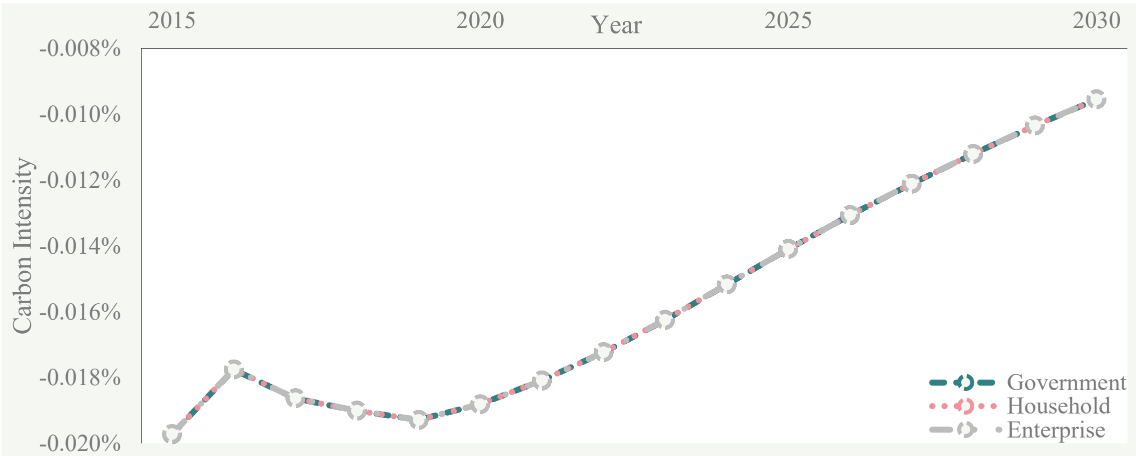


Fig. A2.3 The Health Benefit Impact on the Carbon Intensity under the Revenue Recycling

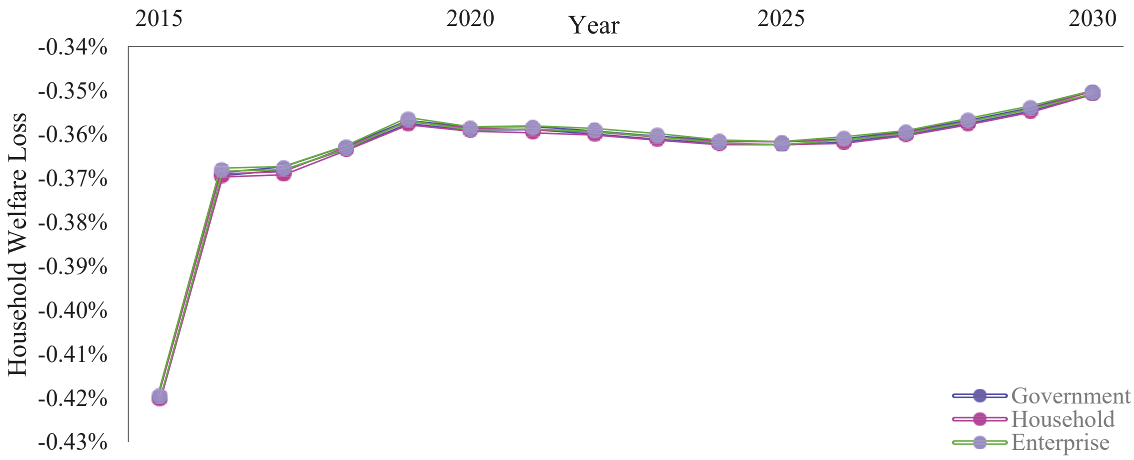


Fig. A2.4 The Health Benefit Impact on the Household Welfare Loss under the Revenue Recycling

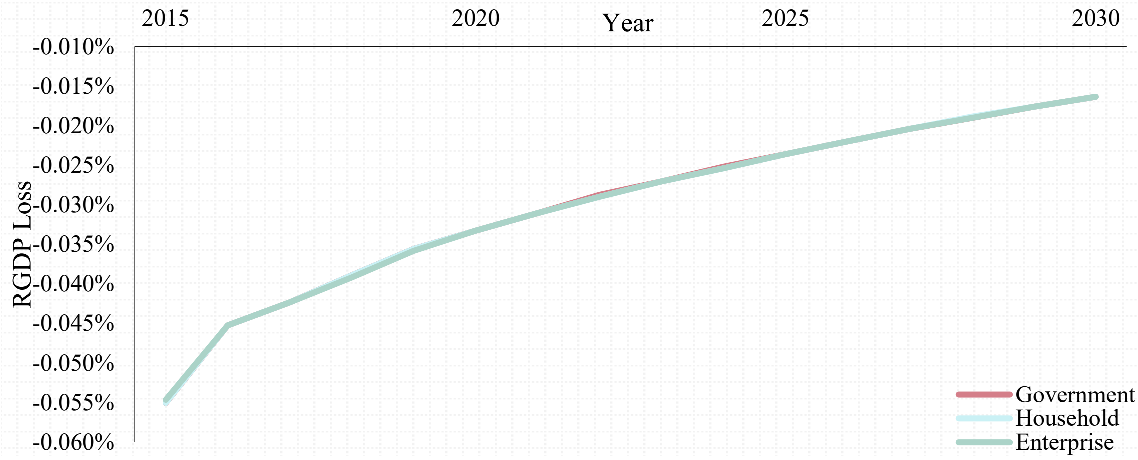


Fig. A2.5 The Health Benefit Impact on the RGDP Loss under the Revenue Recycling

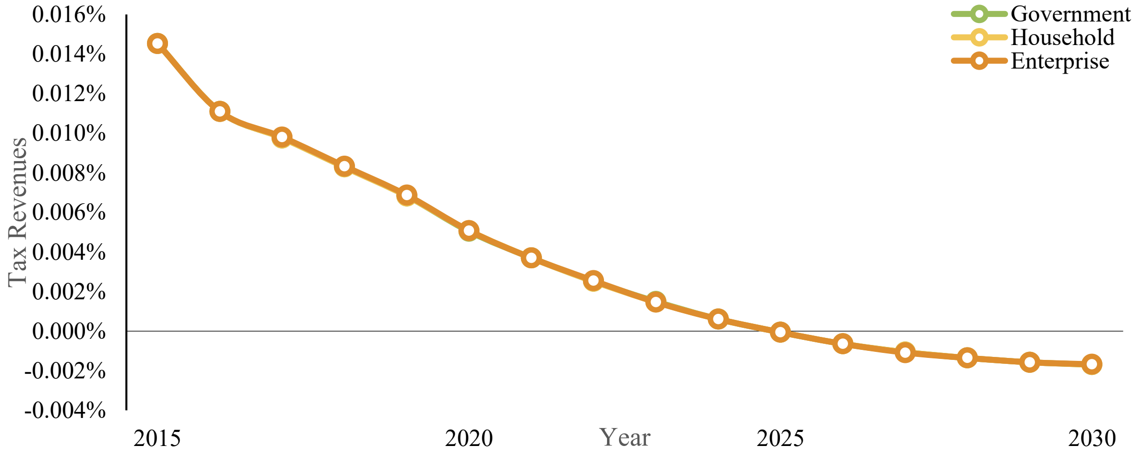


Fig. A2.6 The Health Benefit Impact on the Tax Revenues under the Revenue Recycling

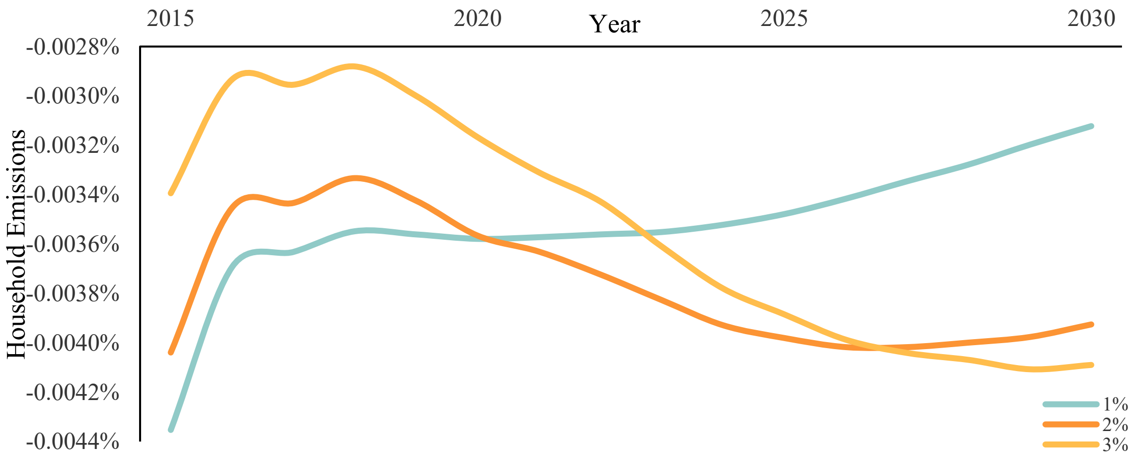


Fig. A4.1 The Household Emission Change in the TL Model Relative to the CD Model

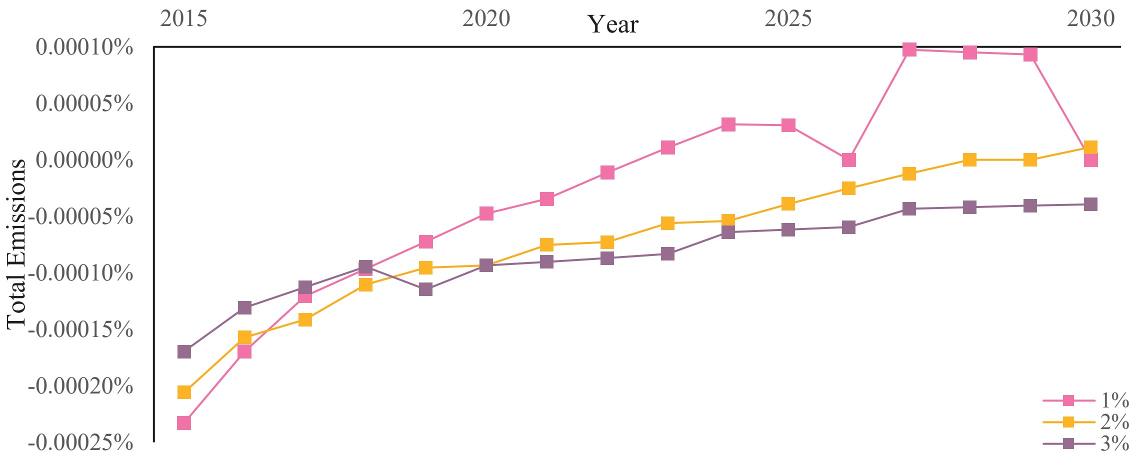


Fig. A4.2 The Total Emission Change in the TL Model Relative to the CD Model

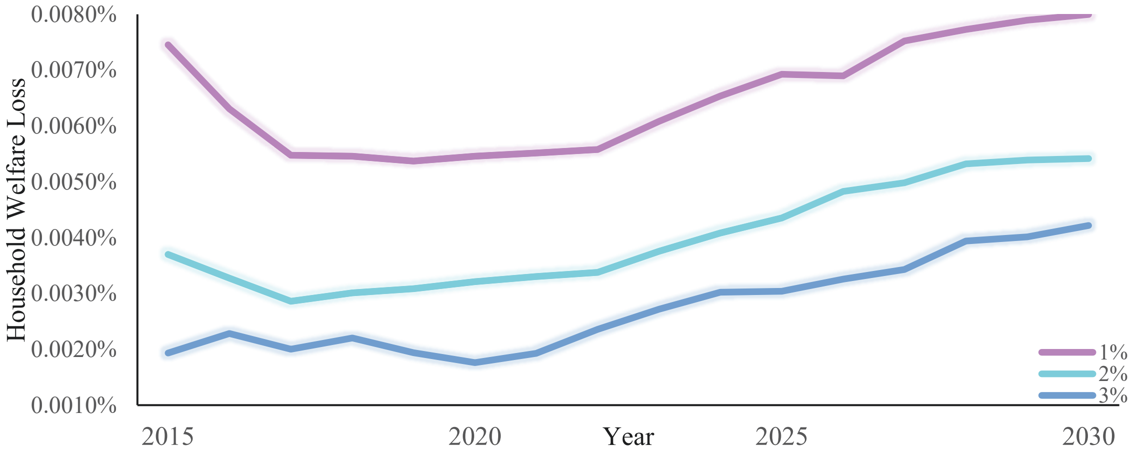


Fig. A4.3 The Household Welfare Loss Change in the TL Model Relative to the CD Model

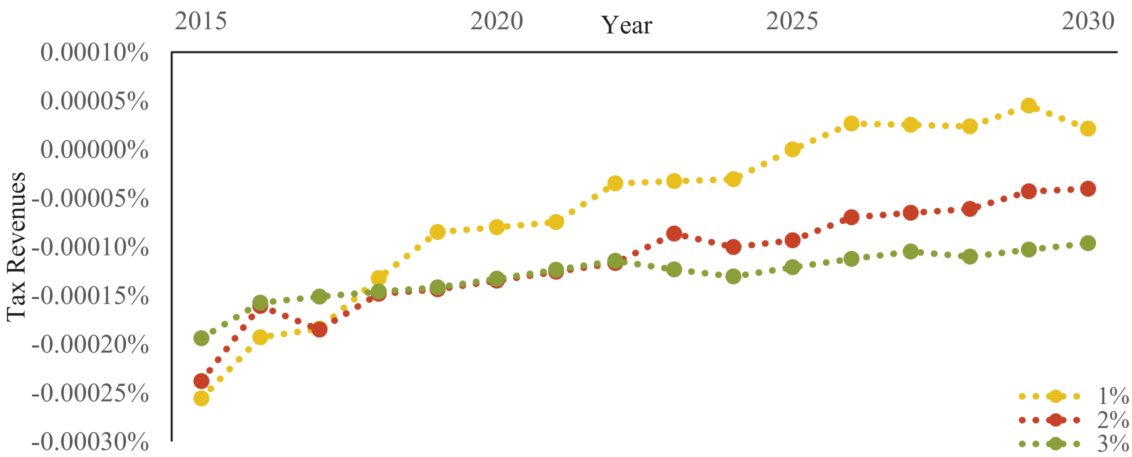


Fig. A4.4 The Tax Revenue Change in the TL Model Relative to the CD Model

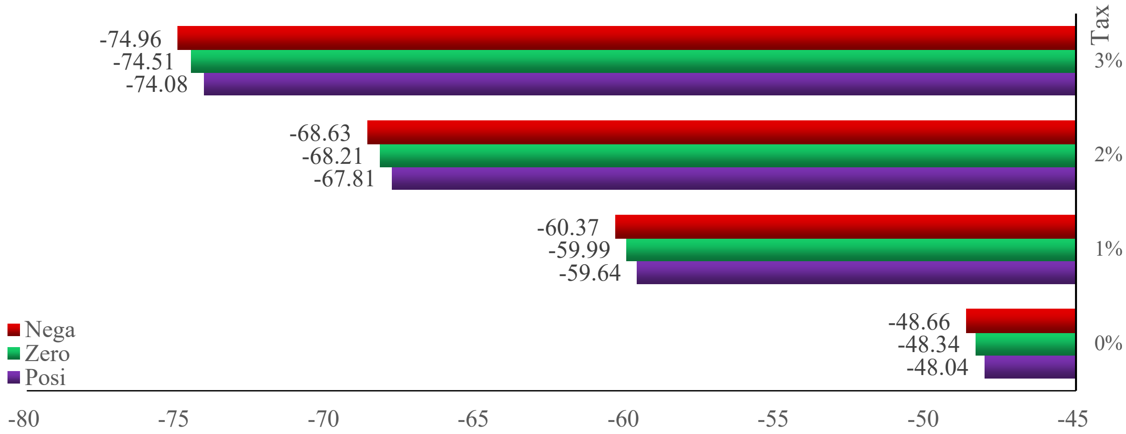


Fig. A5.1 The Relative Utility (RU) in SCRO5 (Unit: 10^9 CNY)

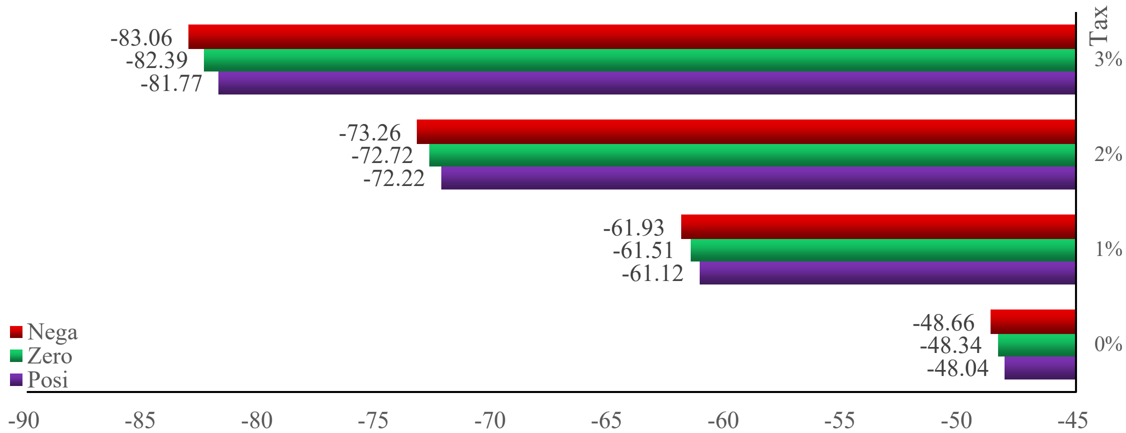


Fig. A5.2 The Relative Utility (RU) in SCRO6 (Unit: 10^9 CNY)

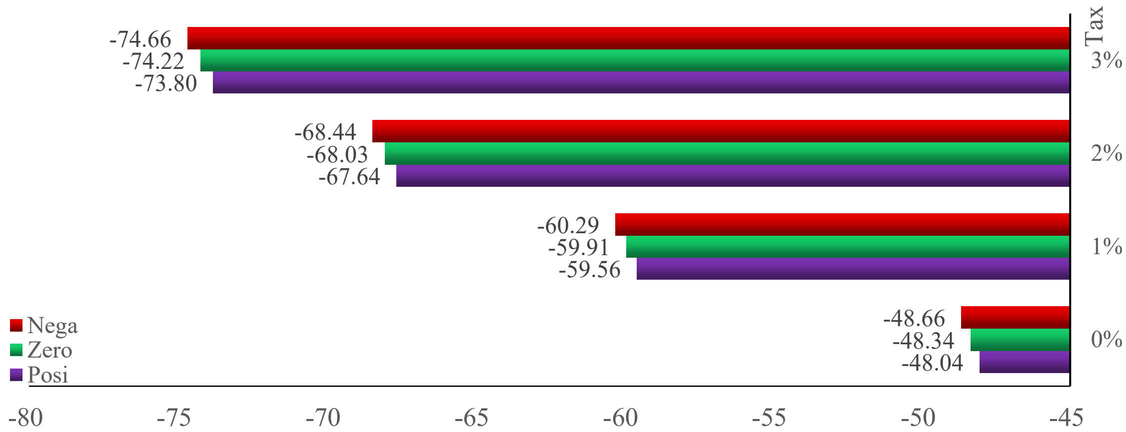


Fig. A5.3 The Relative Utility (RU) in SCRO8 (Unit: 10^9 CNY)

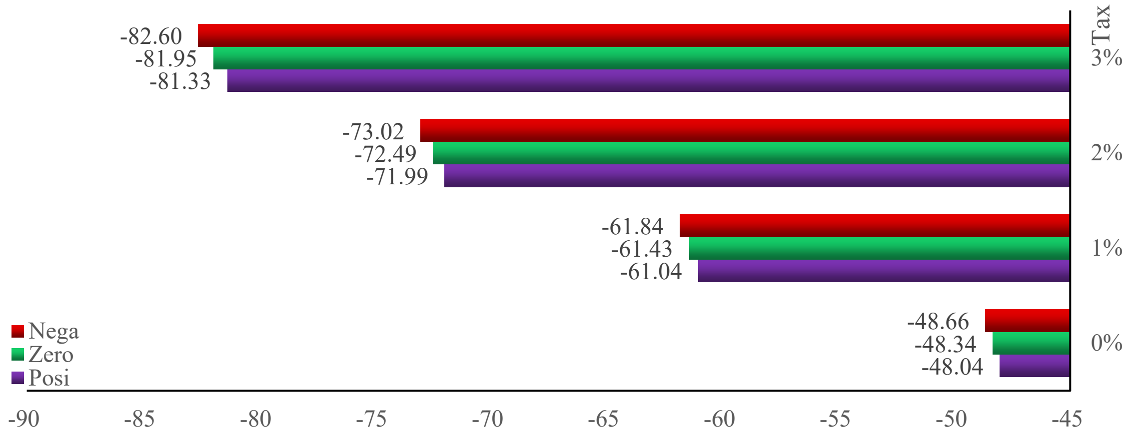


Fig. A5.4 The Relative Utility (RU) in SCRO9 (Unit: 10^9 CNY)

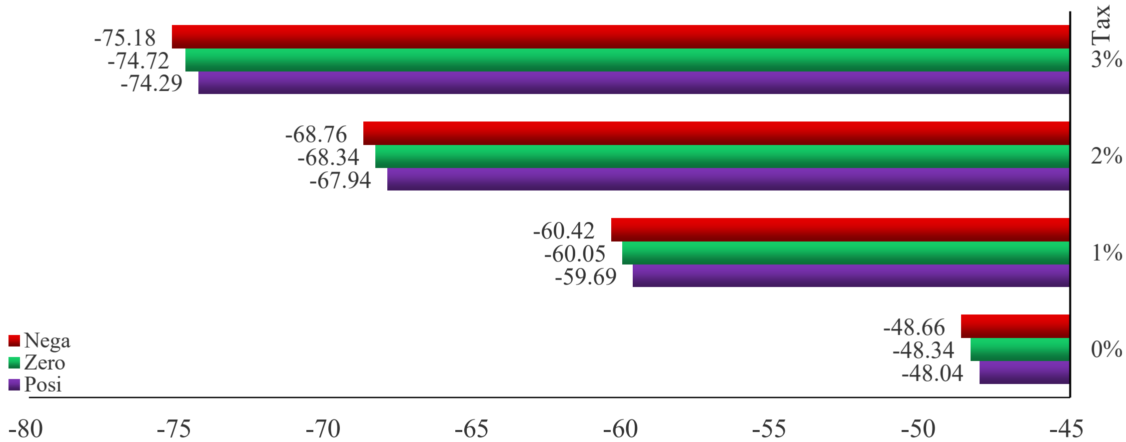


Fig. A5.5 The Relative Utility (RU) in SCRO11 (Unit: 10^9 CNY)

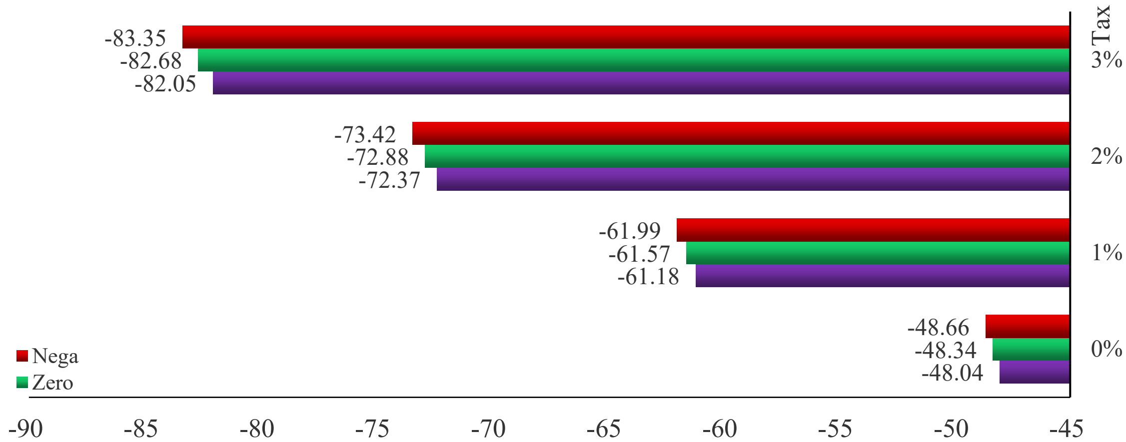


Fig. A5.6 The Relative Utility (RU) in SCRO12 (Unit: 10^9 CNY)

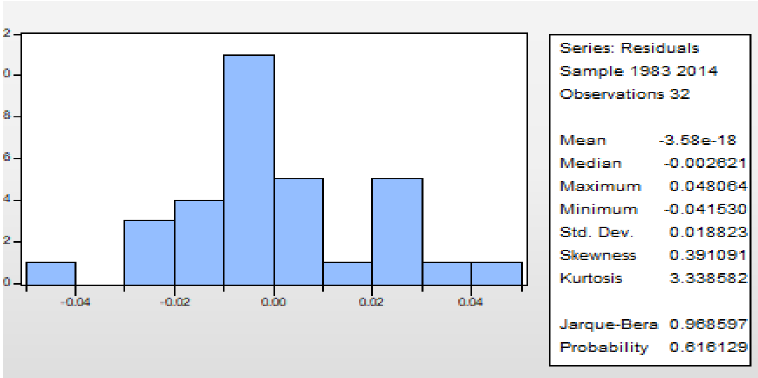


Fig. A6.1 The Histogram Diagnostic for the Residual Normality (Dependent Variable: $\Delta^2 E_t$)

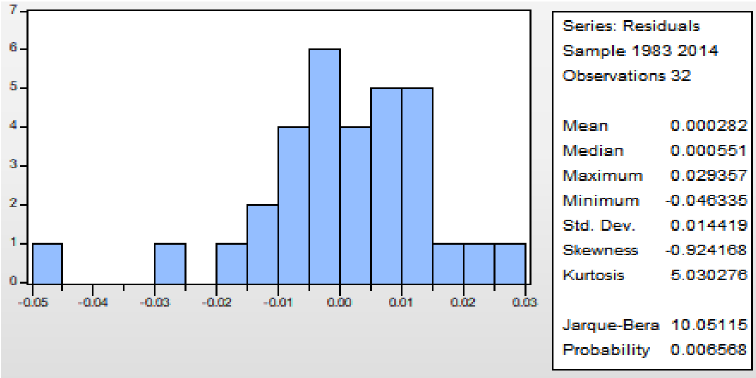


Fig. A6.2 The Histogram Diagnostic for the Residual Normality (Dependent Variable: $\Delta^2 EC_t$)

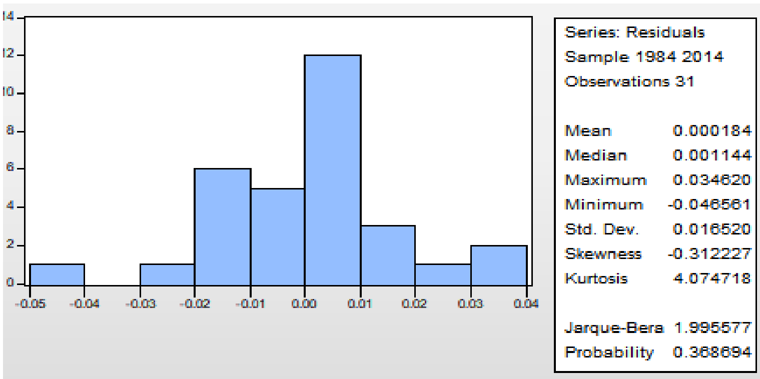


Fig. A6.3 The Histogram Diagnostic for the Residual Normality (Dependent Variable: ΔGDP_t)

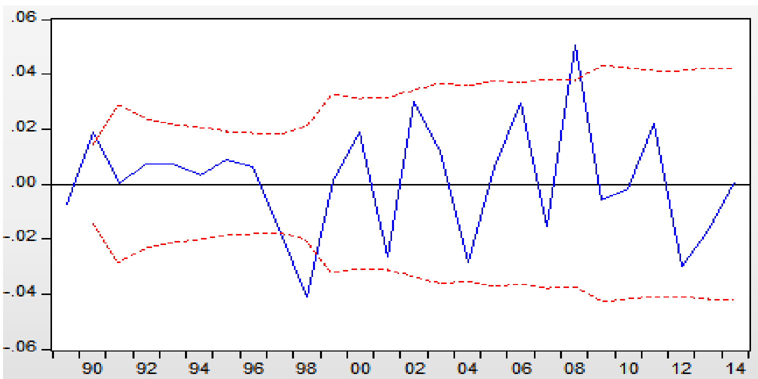


Fig. A6.4 The Recursive Residual Plot (Dependent Variable: $\Delta^2 E_t$)

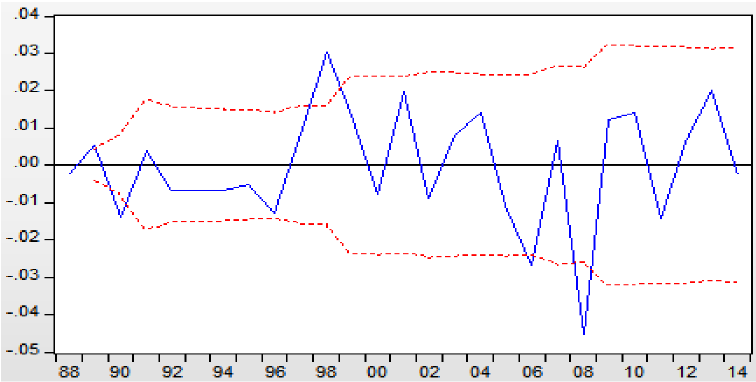


Fig. A6.5 The Recursive Residual Plot (Dependent Variable: $\Delta^2 EC_t$)

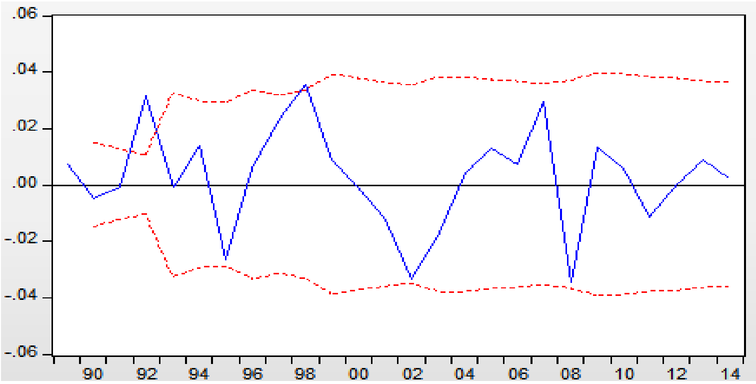


Fig. A6.6 The Recursive Residual Plot (Dependent Variable: ΔGDP_t)

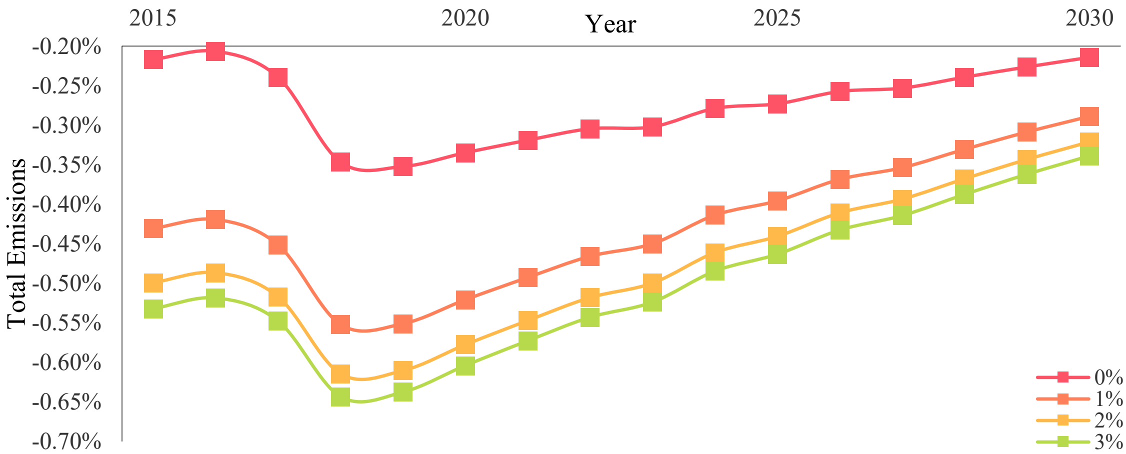


Fig. A6.7 The Urbanisation Impact on the Total Emissions

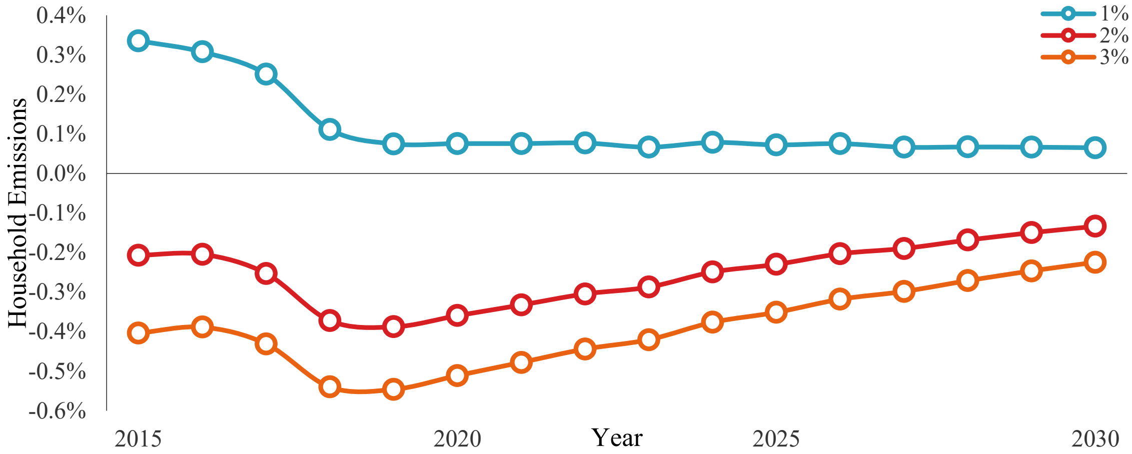


Fig. A6.8 The Relative Change of the Tax Marginal Effect on the Household Emissions

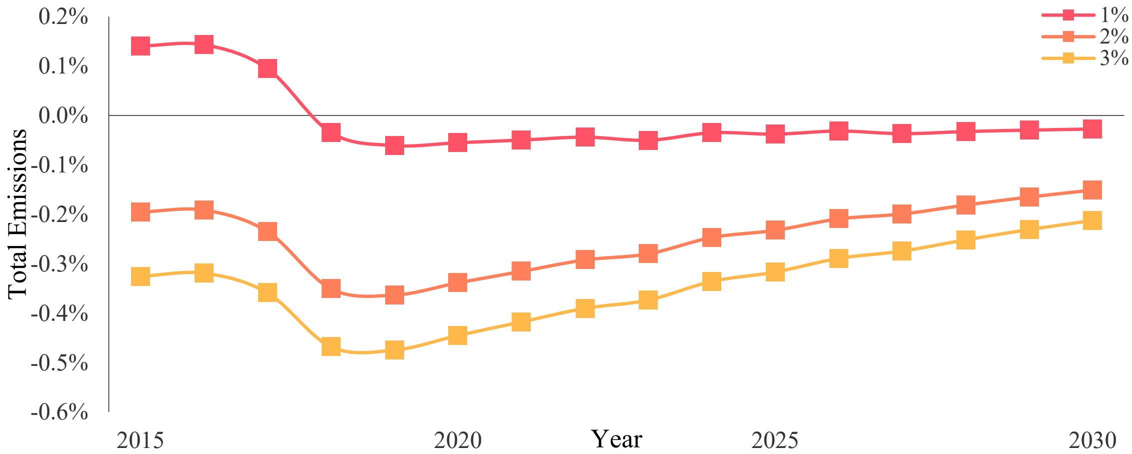


Fig. A6.9 The Relative Change of the Tax Marginal Effect on the Total Emissions

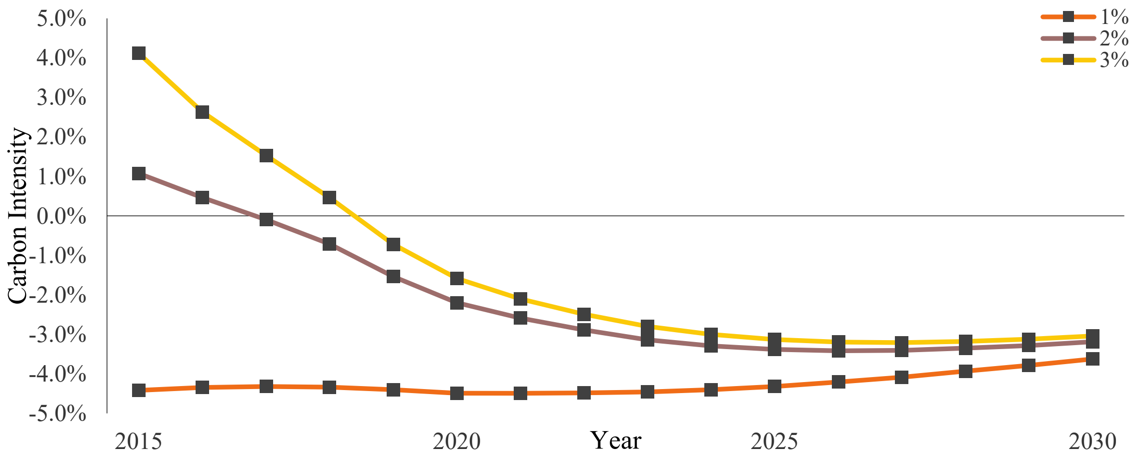


Fig. A6.10 The Relative Change of the Tax Marginal Effect on the Carbon Intensity

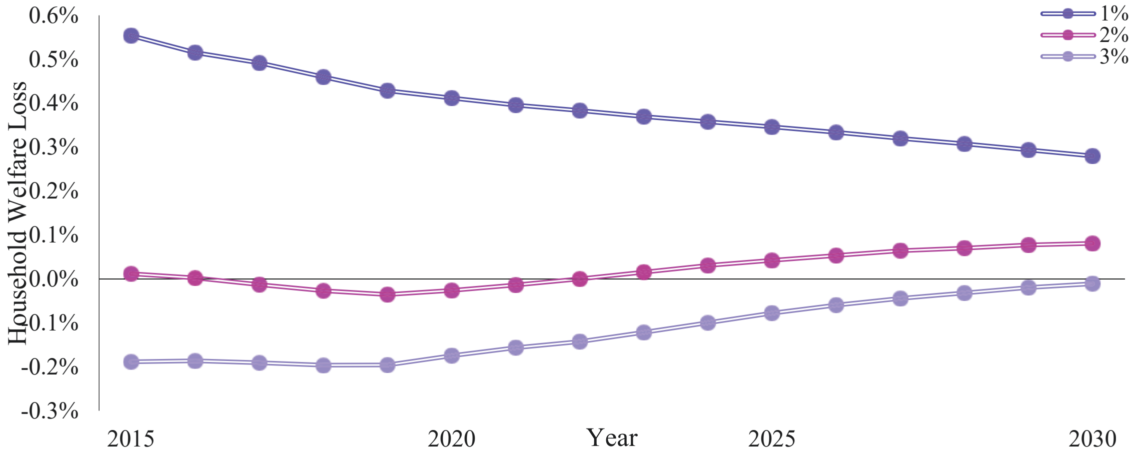


Fig. A6.11 The Relative Change of the Tax Marginal Effect on the Household Welfare Loss

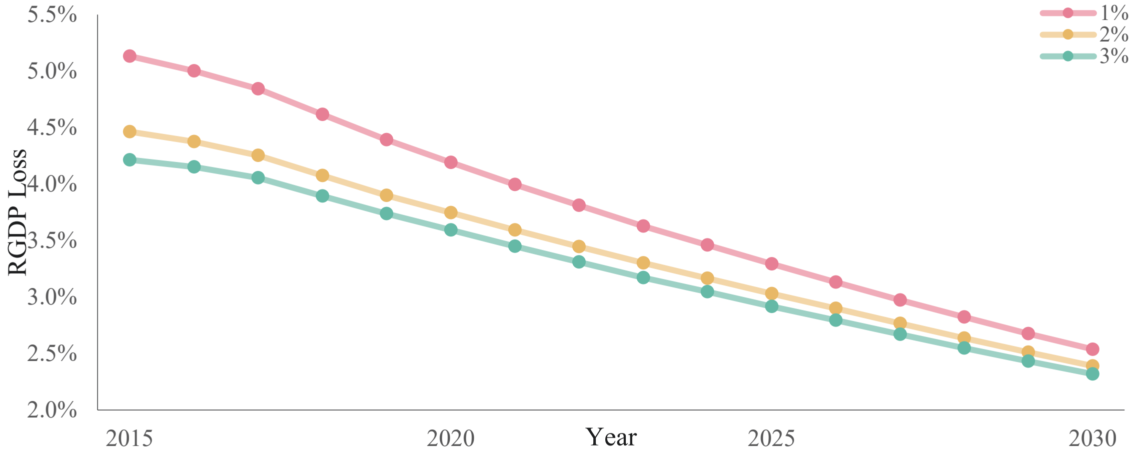


Fig. A6.12 The Relative Change of the Tax Marginal Effect on the RGDP Loss

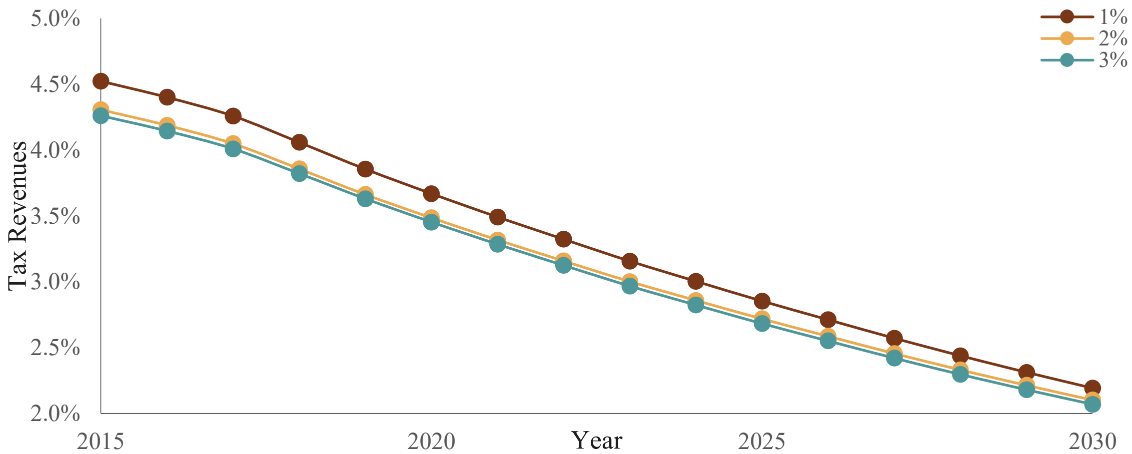


Fig. A6.13 The Relative Change of the Tax Marginal Effect on the Tax Revenues

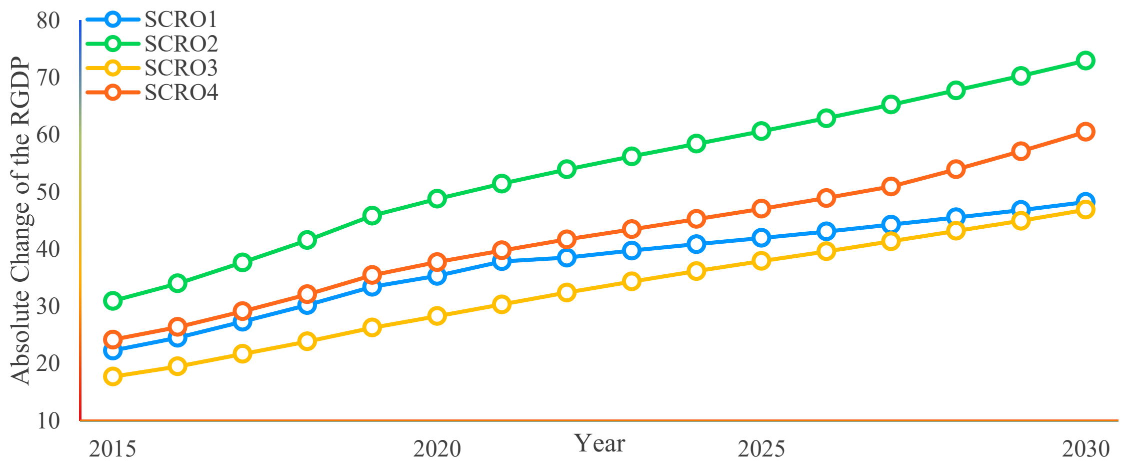


Fig. A7.1 The Absolute Change of the RGDP under the Carbon-cap Policy (Unit: 10^{12} CNY)

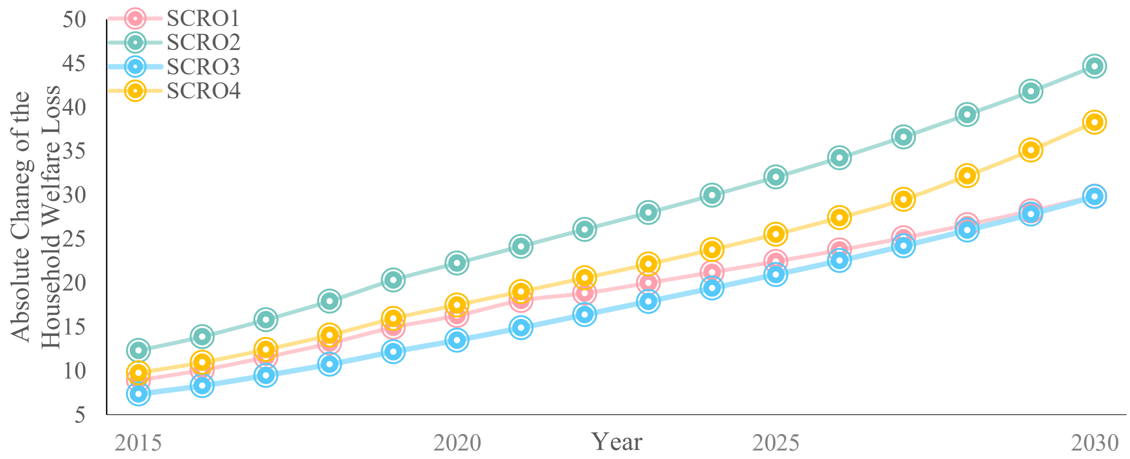


Fig. A7.2 The Absolute Change of the Household Welfare Loss under the Carbon-cap Policy (Unit: 10^{12} CNY)

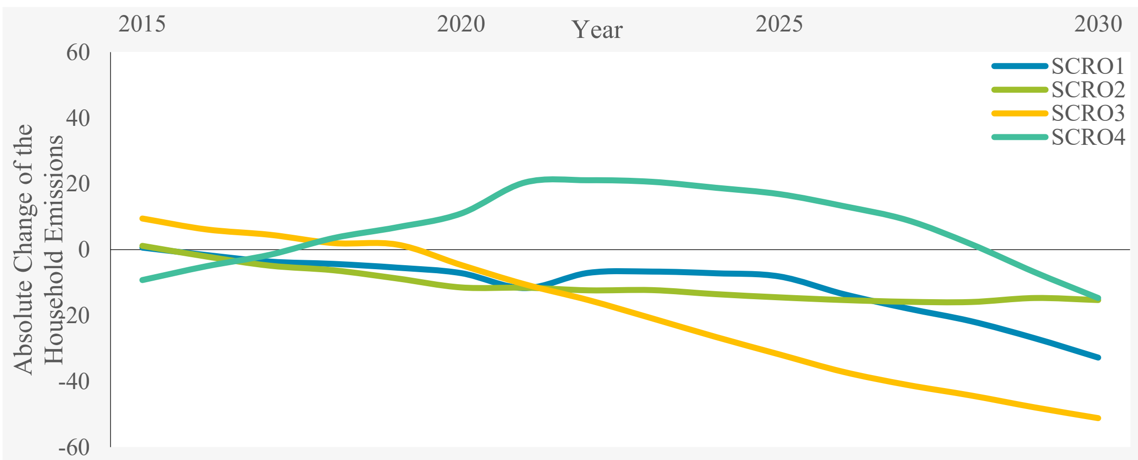


Fig. A7.3 The Absolute Change of the Household Emissions under the Carbon-cap Policy (Unit: 10^6 tonne)

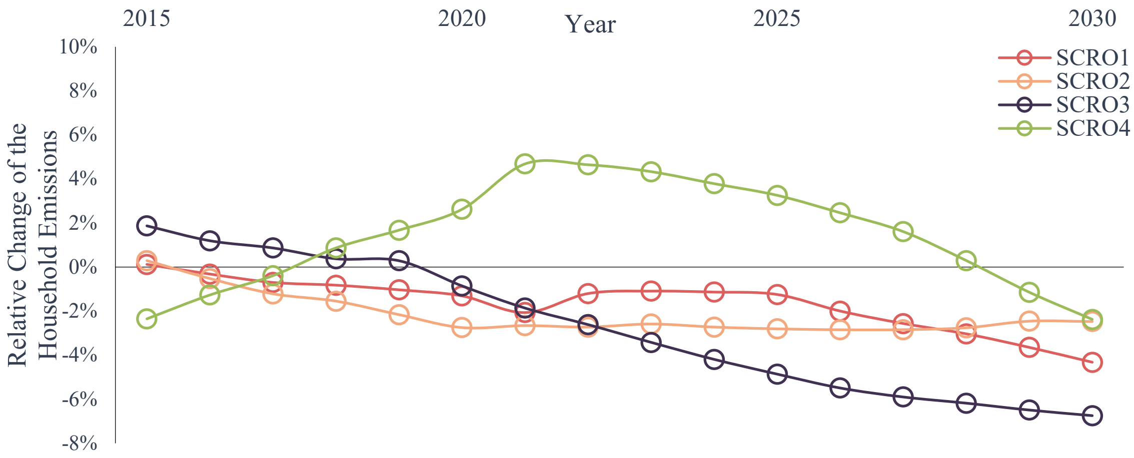


Fig. A7.4 The Relative Change of the Household Emissions under the Carbon-cap Policy

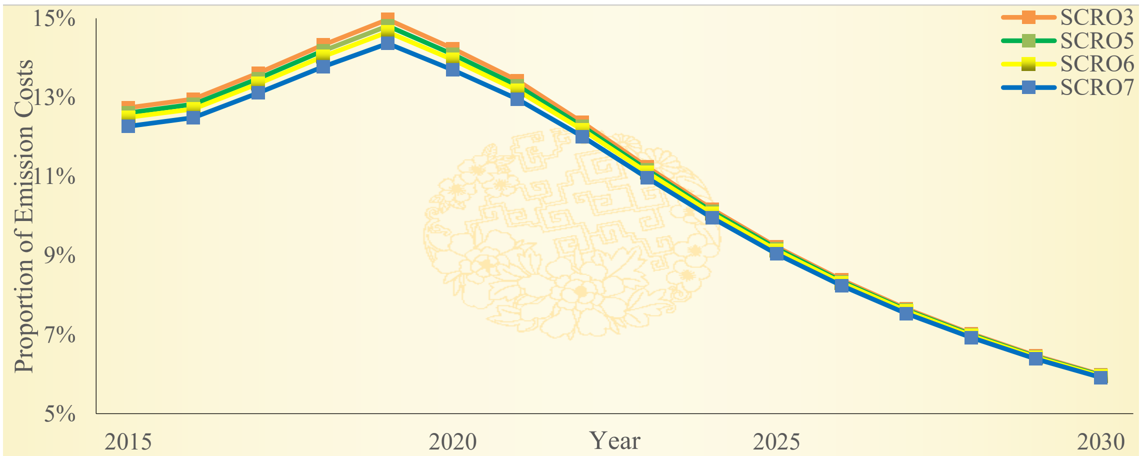


Fig. A7.5 The Proportion of the Overall Emission Costs to the RGDP
Influenced by the Decline Factor

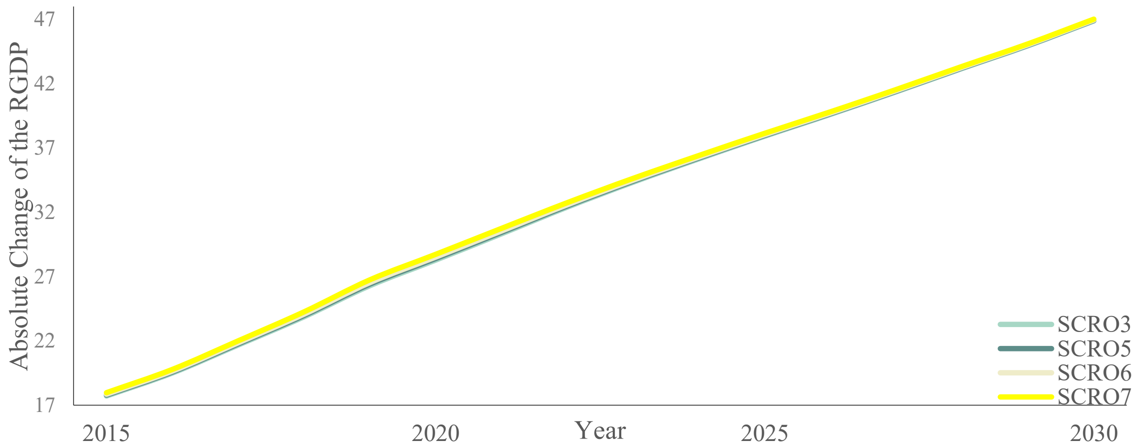


Fig. A7.6 The Absolute Change of the RGDP Influenced by the Decline Factor (Unit: 10^{12} CNY)

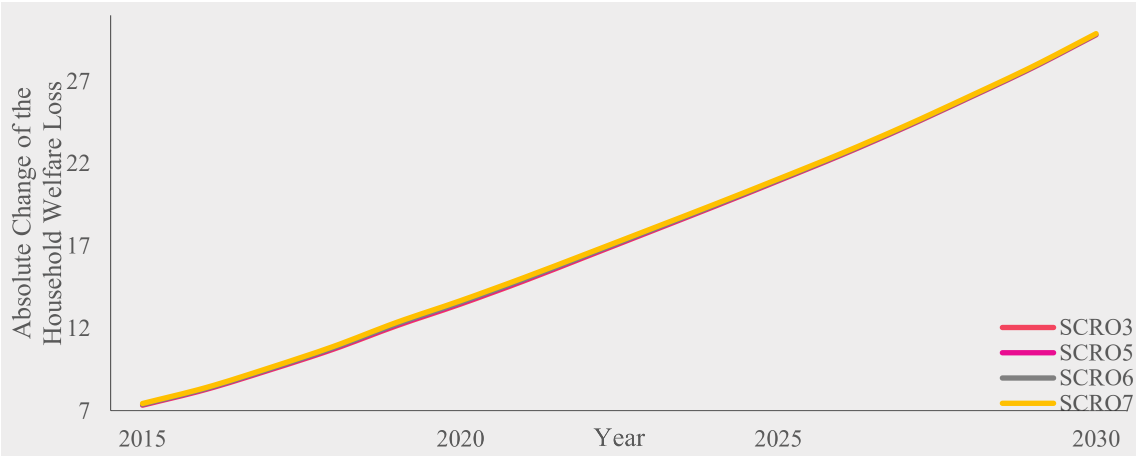


Fig. A7.7 The Absolute Change of the Household Welfare Loss
Influenced by the Decline Factor (Unit: 10^{12} CNY)

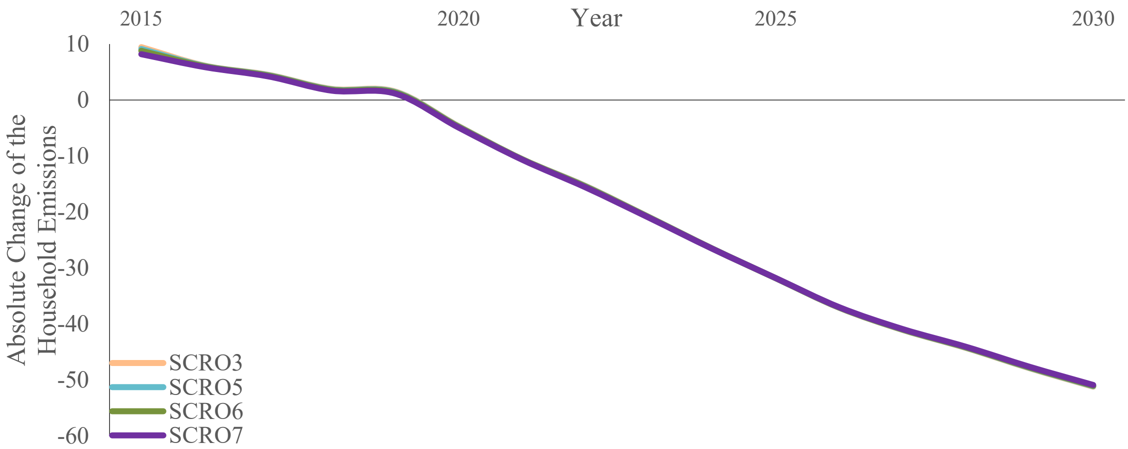


Fig. A7.8 The Absolute Change of the Household Emissions
Influenced by the Decline Factor (Unit: 10^6 tonne)

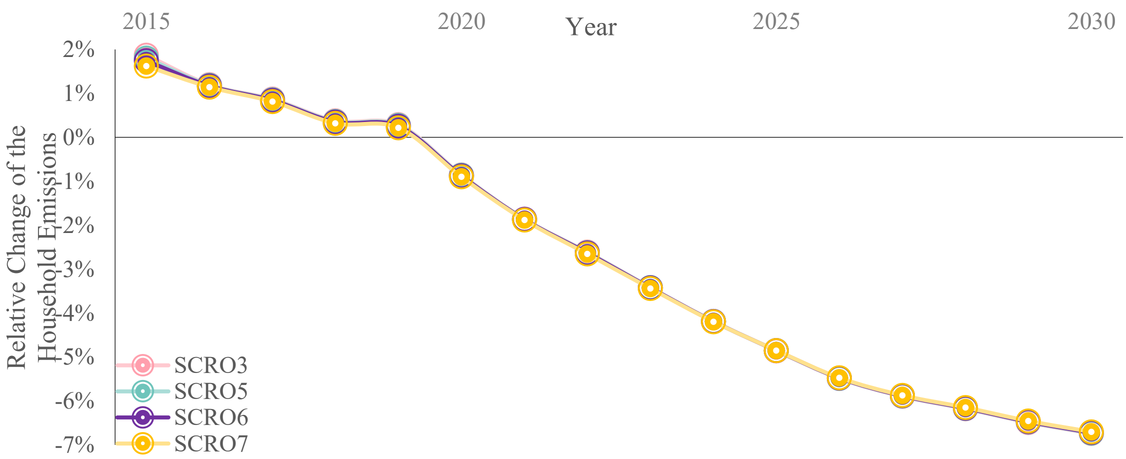


Fig. A7.9 The Relative Change of the Household Emissions Influenced by the Decline Factor

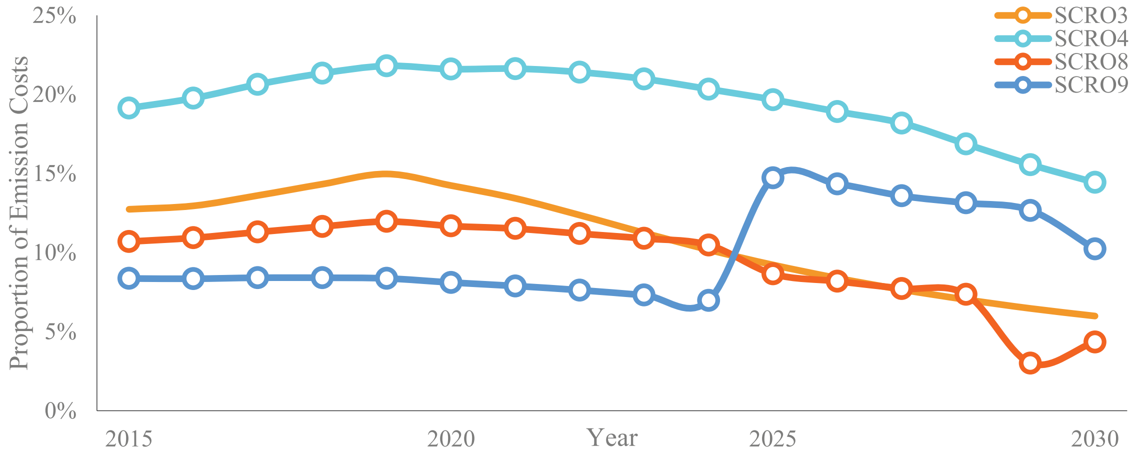


Fig. A7.10 The Proportion of the Overall Emission Costs to the RGDP under the Carbon Trading

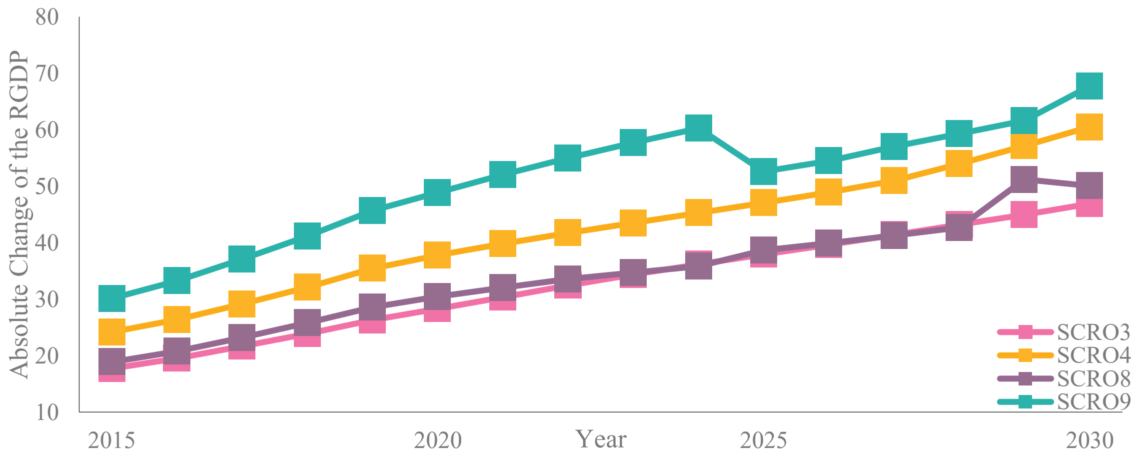


Fig. A7.11 The Absolute Change of the RGDP under the Carbon Trading (Unit: 10^{12} CNY)

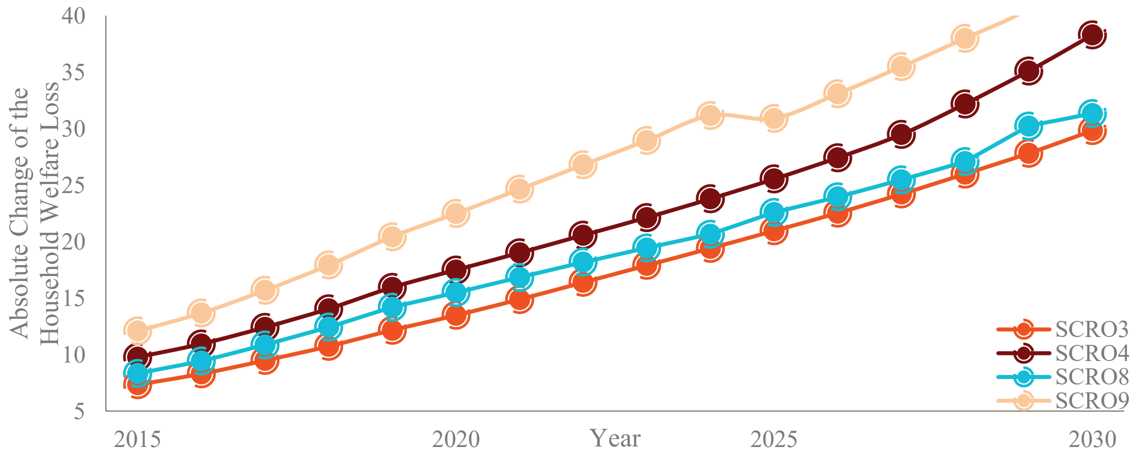


Fig. A7.12 The Absolute Change of the Household Welfare Loss under the Carbon Trading (Unit: 10^{12} CNY)

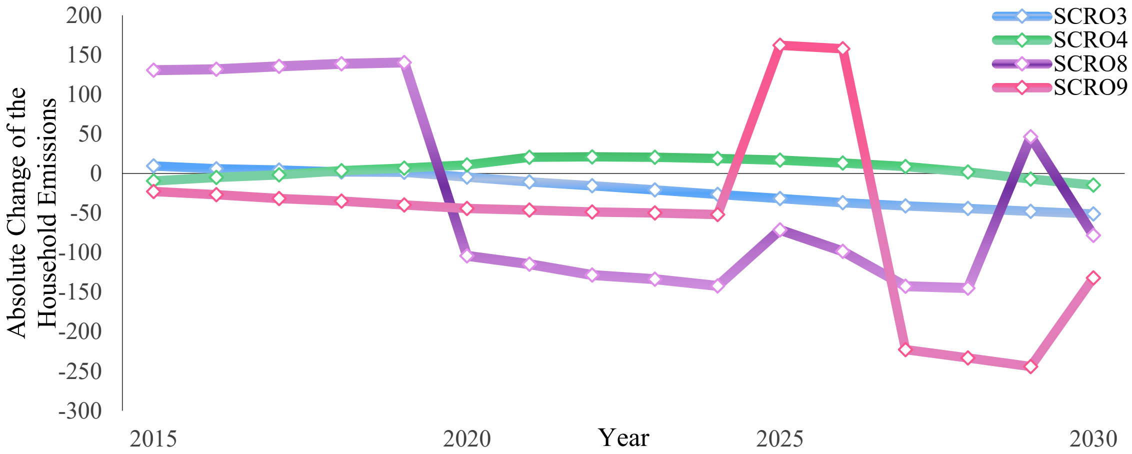


Fig. A7.13 The Absolute Change of the Household Emissions under the Carbon Trading (Unit: 10^6 tonne)

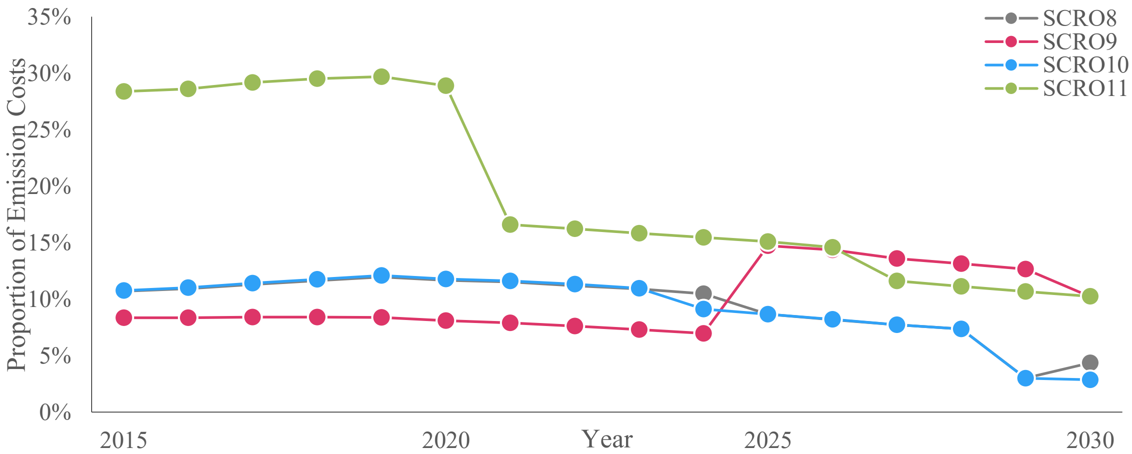


Fig. A7.14 The Proportion of the Overall Emission Costs to the RGDP under Banning the FCQ Trading

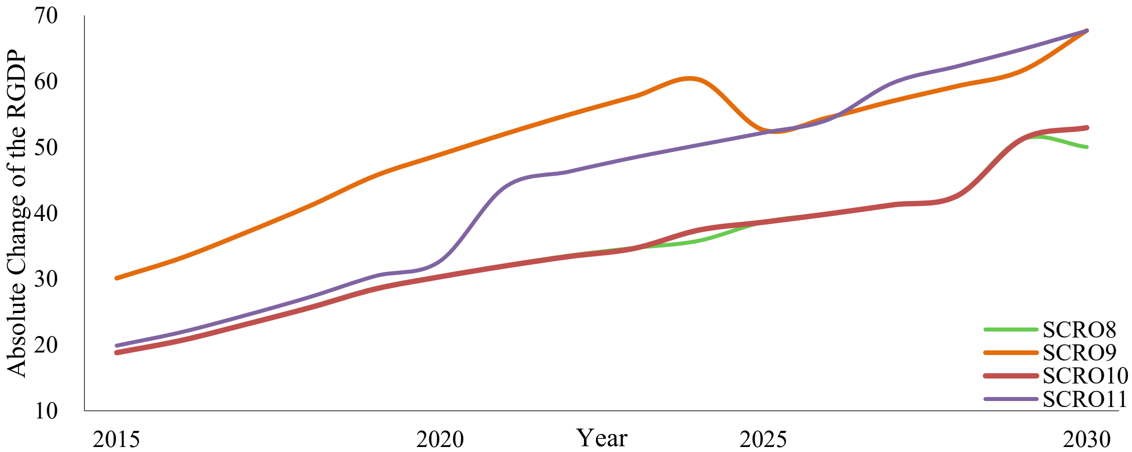


Fig. A7.15 The Absolute Change of the RGDP under Banning the FCQ Trading (Unit: 10^{12} CNY)

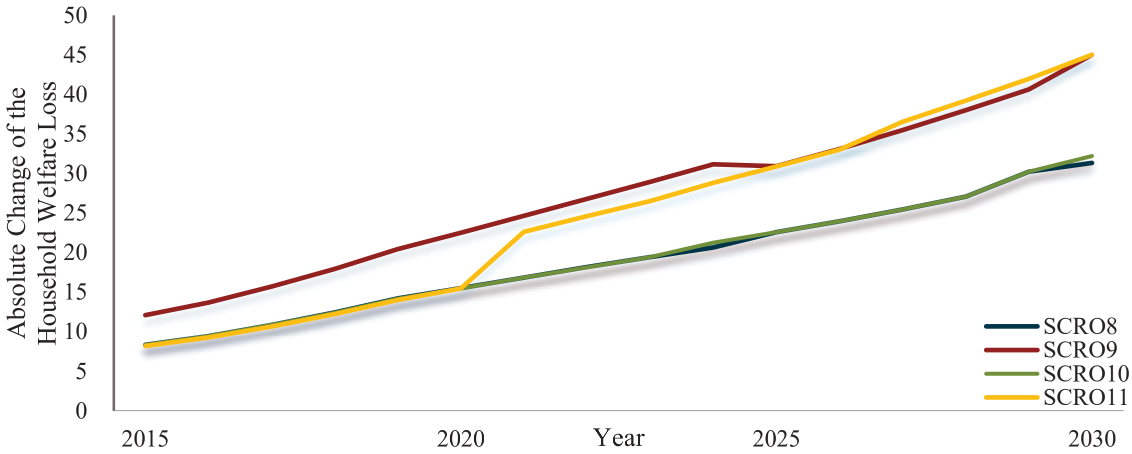


Fig. A7.16 The Absolute Change of the Household Welfare Loss
under Banning the FCQ Trading (Unit: 10^{12} CNY)

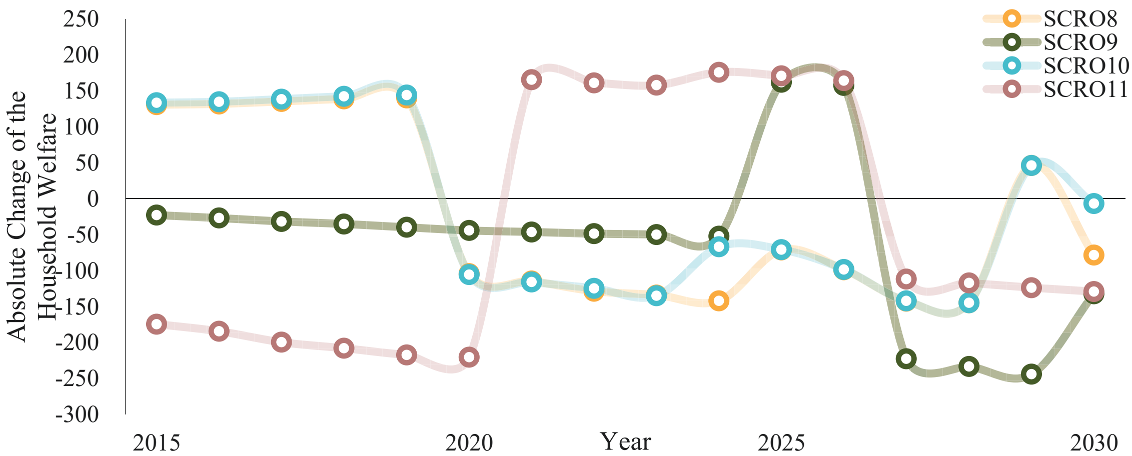


Fig. A7.17 The Absolute Change of the Household Emissions
under Banning the FCQ Trading (Unit: 10^{6} tonne)

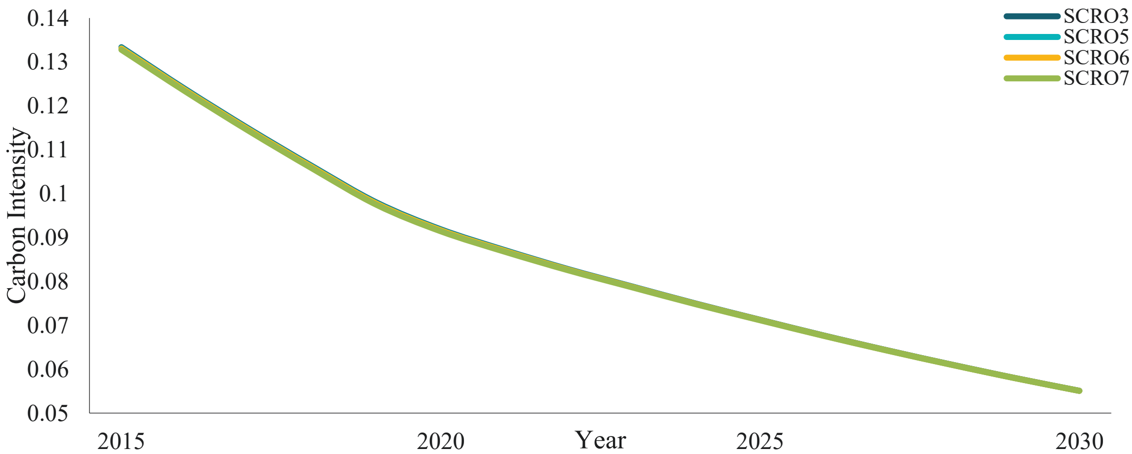


Fig. A7.18 The Carbon Intensity Influenced by the Decline Factor (Unit: kg/CNY)

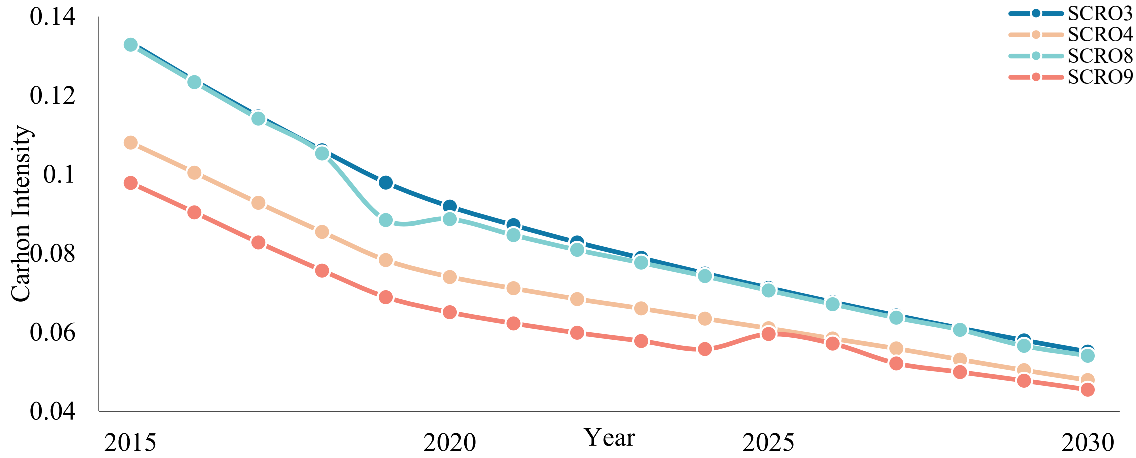


Fig. A7.19 The Carbon Intensity under the Carbon Trading (Unit: kg/CNY)

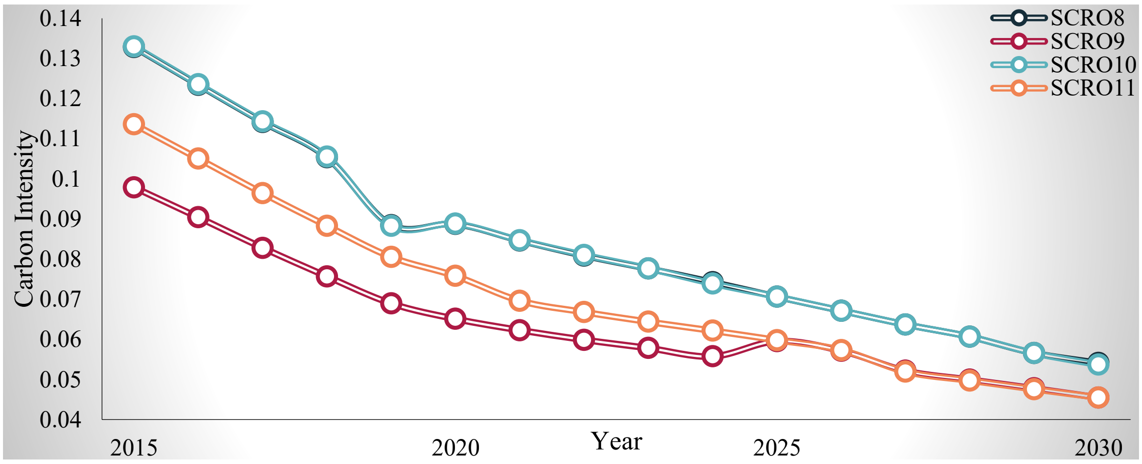


Fig. A7.20 The Carbon Intensity under Banning the FCQ Trading (Unit: kg/CNY)

Appendix B: Equations in the CGE Model

Table B1 The Sector Abbreviations (Abbr) in the CGE Equations

Sector	Abbr	Sector	Abbr	Sector	Abbr
Agriculture Industry	agric	Construction Industry	const	Electricity Transmission	TD
Other Mining Industry	othm	Transport and Storage	trans	Supercrit-coal Electricity	Supercrit
Food and Tobacco	food	Service	service	USC-coal Electricity	USC
Textile	texti	Coal Mining	coalm	Subc-coal Electricity	subc
Furniture	furni	Coking	coking	Gas Electricity	NG
Chemical Industry	chemical	Petroleum Mining	petrm	Nuclear Electricity	Nuclear
Mineral Products	mineral	Petroleum Processing	petrp	Hydro Electricity	Hydro
Metal Products	metal	Gas Mining	gasn	Wind Electricity	wind
Machinery	machi	Gas Production	gasm	Solar Electricity	solarpv
Water Production	water	Fire power	fipow		

Table B2 The Energy Abbreviations (Abbr) in the CGE Equations

Energy	Abbr	Energy	Abbr	Energy	Abbr
Coal	Fuel1	Fuel Oil	Fuel7	Natural-gas Electricity	Fuel13
Charcoal	Fuel2	Natural Gas	Fuel8	Nuclear Electricity	Fuel14
Crude Oil	Fuel3	Electricity Transmission	Fuel9	Hydro Electricity	Fuel15
Kerosene	Fuel4	Supercrit-coal Electricity	Fuel10	Wind Electricity	Fuel16
Gasoline	Fuel5	USC-coal Electricity	Fuel11	Solar Electricty	Fuel17
Diesel Oil	Fuel6	Subc-coal Electricity	Fuel12		

*******************************Production Function *******************************

$UND_{oths,it} = ca_{oths,it} \times ND_{it};$

$PND_{it} = \sum_{oths}(ca_{oths,it} \times PQ_{oths,t});$

$ND_{it} = deltaND_{it}^{\frac{1}{1-parQX_{it}}} \times (\frac{PX_{it}}{PND_{it}})^{\frac{1}{1-parQX_{it}}} \times QX_{it};$

$KEL_{it} = deltaKEL_{it}^{\frac{1}{1-parQX_{it}}} \times (\frac{PX_{it}}{PKEL_{it}})^{\frac{1}{1-parQX_{it}}} \times QX_{it};$

$QX_{it} = (deltaKEL_{it} \times KEL_{it}^{parQX_{it}} + deltaND_{it} \times ND_{it}^{parQX_{it}})^{1/parQX_{it}};$

$KE_{it} = (scaleKEL_{it}^{parKEL_{it}} \times deltaKE_{it} \times \frac{PKEL_{it}}{PKE_{it}})^{\frac{1}{1-parKEL_{it}}} \times KEL_{it};$

$WL_t \times wldist_{it} = PKEL_{it} \times KEL_{it} \times (deltaKE_{it} \times KE_{it}^{parKEL_{it}} + deltaL_{it} \times L_{it}^{parKEL_{it}})^{-1} \times deltaL_{it} \times L_{it}^{parKEL_{it}-1};$

$KEL_{it} = scaleKEL_{it} \times (deltaKE_{it} \times KE_{it}^{parKEL_{it}} + deltaL_{it} \times L_{it}^{parKEL_{it}})^{1/parKEL_{it}};$

$E_{it} = (scaleKE_{it}^{parKE_{it}} \times deltaE_{it} \times \frac{PKE_{it}}{PE_{it}})^{\frac{1}{1-parKE_{it}}} \times KE_{it};$

$WK_t \times wrdist_{it} = PKE_{it} \times KE_{it} \times (deltaK_{it} \times K_{it}^{parKE_{it}} + deltaE_{it} \times E_{it}^{parKE_{it}})^{-1} \times deltaK_{it} \times K_{it}^{parKE_{it}-1};$

$KE_{it} = scaleKE_{it} \times (deltaK_{it} \times K_{it}^{parKE_{it}} + deltaE_{it} \times E_{it}^{parKE_{it}})^{1/parKE_{it}};$

$Efos_{it} = deltafos_{it}^{\frac{1}{1-parE_{it}}} \times (\frac{PE_{it}}{PEfos_{it}})^{\frac{1}{1-parE_{it}}} \times E_{it};$

$Epow_{it} = deltapow_{it}^{\frac{1}{1-parE_{it}}} \times (\frac{PE_{it}}{PEpow_{it}})^{\frac{1}{1-parE_{it}}} \times E_{it};$

$E_{it} = (deltafos_{it} \times Efos_{it}^{parE_{it}} + dpow_{it} \times Epow_{it}^{parE_{it}})^{1/parE_{it}};$

$$Ecoal_{it} = deltacoal_{it}^{\frac{1}{1-parCPG_{it}}} \times (\frac{PEfos_{it}}{PEcoal_{it}})^{\frac{1}{1-parCPG_{it}}} \times Efos_{it};$$
$$Epg_{it} = deltapg_{it}^{\frac{1}{1-parCPG_{it}}} \times (\frac{PEfos_{it}}{PEpg_{it}})^{\frac{1}{1-parCPG_{it}}} \times Efos_{it};$$
$$Efos_{it} = (deltacoal_{it} \times Ecoal_{it}^{parCPG_{it}} + deltapg_{it} \times Epg_{it}^{parCPG_{it}})^{1/parE_{it}};$$
$$Epetr_{it} = deltapetr_{it}^{\frac{1}{1-parPG_{it}}} \times (\frac{PEpg_{it}}{PEpetr_{it}})^{\frac{1}{1-parPG_{it}}} \times Epg_{it};$$
$$EFuel8_{it} = deltaFuel8_{it}^{\frac{1}{1-parPG_{it}}} \times (\frac{PEpg_{it}}{PEFuel8_{it}})^{\frac{1}{1-parPG_{it}}} \times Epg_{it};$$
$$Epg_{it} = (deltapetr_{it} \times Epetr_{it}^{parPG_{it}} + deltaFuel8_{it} \times EFuel8_{it}^{parPG_{it}})^{1/parPG_{it}};$$
$$EFuel1_{it} = deltaFuel1_{it}^{\frac{1}{1-parcoal_{it}}} \times \frac{PEcoal_{it}}{PQ_{"coalm",t} \times (1+tc_{"coalm",t})}^{\frac{1}{1-parcoal_{it}}} \times Ecoal_{it};$$
$$EFuel2_{it} = deltaFuel2_{it}^{\frac{1}{1-parcoal_{it}}} \times \frac{PEcoal_{it}}{PQ_{"coking",t} \times (1+tc_{"coking",t})}^{\frac{1}{1-parcoal_{it}}} \times Ecoal_{it};$$
$$Ecoal_{it} = (deltaFuel1_{it} \times EFuel1_{it}^{parcoal_{it}} + deltaFuel2_{it} \times EFuel2_{it}^{parcoal_{it}})^{1/parcoal_{it}};$$
$$Egasn_{it} = deltagasn_{it}^{\frac{1}{1-pargas_{it}}} \times \frac{PEgas_{it}}{PQ_{"gasn",t}}^{\frac{1}{1-pargas_{it}}} \times EFuel8_{it};$$
$$Egasm_{it} = deltagasm_{it}^{\frac{1}{1-pargas_{it}}} \times \frac{PEgas_{it}}{PQ_{"gasm",t}}^{\frac{1}{1-pargas_{it}}} \times EFuel8_{it};$$
$$EFuel8_{it} = (deltagasn_{it} \times Egasn_{it}^{pargas_{it}} + deltagasm_{it} \times Egasm_{it}^{pargas_{it}})^{1/pargas_{it}};$$
$$EFuel3_{it} = deltaFuel3_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEpetr_{it}}{PQ_{"pertm",t} \times (1+tc_{"petrm",t})}^{\frac{1}{1-parpetr_{it}}} \times Epetr_{it};$$
$$Epetrp_{it} = deltapetrp_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEpetr_{it}}{PEpetrp_{it}}^{\frac{1}{1-parpetr_{it}}} \times Epetr_{it};$$
$$Epetr_{it} = (deltaFuel3_{it} \times EFuel3_{it}^{parpetr_{it}} + deltapetrp_{it} \times Epetrp_{it}^{parpetr_{it}})^{1/parpetr_{it}};$$
$$EFuel4_{it} = deltaFuel4_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEpetrp_{it}}{PQ_{"petrp",t} \times (1+tc_{"petrp",t})}^{\frac{1}{1-parpetr_{it}}} \times Epetrp_{it};$$
$$EFuel5\_6\_7_{it} = deltaFuel5\_6\_7_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEpetrp_{it}}{PEFuel5\_6\_7_{it}}^{\frac{1}{1-parpetr_{it}}} \times Epetrp_{it};$$
$$Epetrp_{it} = (deltaFuel4_{it} \times EFuel4_{it}^{parpetr_{it}} + deltaFuel5\_6\_7_{it} \times EFuel5\_6\_7_{it}^{parpetr_{it}})^{\frac{1}{parpetr_{it}}};$$
$$EFuel5_{it} = deltaFuel5_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEFuel5\_6\_7_{it}}{PQ_{"petrp",t} \times (1+tc_{"petrp",t})}^{\frac{1}{1-parpetr_{it}}} \times EFuel5\_6\_7_{it};$$
$$EFuel6\_7_{it} = deltaFuel6\_7_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEFuel5\_6\_7_{it}}{PEFuel6\_7_{it}}^{\frac{1}{1-parpetr_{it}}} \times EFuel5\_6\_7_{it};$$
$$EFuel5\_6\_7_{it} = (deltaFuel5_{it} \times EFuel5_{it}^{parpetr_{it}} + deltaFuel6\_7_{it} \times EFuel6\_7_{it}^{parpetr_{it}})^{1/parpetr_{it}};$$
$$EFuel6_{it} = deltaFuel6_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEFuel6\_7_{it}}{PQ_{"petrp",t} \times (1+tc_{"petrp",t})}^{\frac{1}{1-parpetr_{it}}} \times EFuel6\_7_{it};$$
$$EFuel7_{it} = deltaFuel6\_7_{it}^{\frac{1}{1-parpetr_{it}}} \times \frac{PEFuel6\_7_{it}}{PQ_{"petrp",t} \times (1+tc_{"petrp",t})}^{\frac{1}{1-parpetr_{it}}} \times EFuel6\_7_{it};$$
$$EFuel6\_7_{it} = (deltaFuel6_{it} \times EFuel6_{it}^{parpetr_{it}} + deltaFuel7_{it} \times EFuel7_{it}^{parpetr_{it}})^{1/parpetr_{it}};$$
$$Efipow_{it} = deltafipow_{it}^{\frac{1}{1-parpow_{it}}} \times \frac{PEpow_{it}}{PQ_{"fipow",t}}^{\frac{1}{1-parpow_{it}}} \times Epow_{it};$$
$$Eelec_{it} = deltaelec_{it}^{\frac{1}{1-parpow_{it}}} \times (\frac{PEpow_{it}}{Pelec_t})^{\frac{1}{1-parpow_{it}}} \times Epow_{it};$$
$$Epow_{it} = (deltafipow_{it} \times Efipow_{it}^{parpow_{it}} + deltaelec_{it} \times Eelec_{it}^{parpow_{it}})^{1/parpow_{it}}.$$

The subscript i refers to a sector; $oths$ refers to a nonenergy sector excluding the fire power sector; t refers to a year.

$ca_{oths,it}$ is the Chinese direct consumption coefficient in the input-output table.
$deltacoal_{it}$ is the share of the coal composite input.
$deltaE_{it}$ is the share of the energy composite input.
$deltaelec_{it}$ is the share of the electricity composite input.
$deltafipow_{it}$ is the share of the heat input.
$deltafos_{it}$ is the share of the fossil composite input.
$deltaFuel1_{it}$ is the share of the coal mining input.
$deltaFuel2_{it}$ is the share of the charcoal input.
$deltaFuel3_{it}$ is the share of the crude oil input.
$deltaFuel4_{it}$ is the share of the kerosene input.
$deltaFuel5_{it}$ is the share of the gasoline input.
$deltaFuel5\_6\_7_{it}$ is the share of the gasoline-diesel-fuel-oil composite input.
$deltaFuel6_{it}$ is the share of the diesel oil input.
$deltaFuel6\_7_{it}$ is the share of the diesel-fuel-oil composite input.
$deltaFuel7_{it}$ is the share of the fuel oil input.
$deltaFuel8_{it}$ is the share of the gas composite input.
$deltagasm_{it}$ is the share of the gas input.
$deltagasn_{it}$ is the share of the natural gas input.
$deltaK_{it}$ is the share of the capital input.
$deltaKE_{it}$ is the share of the capital-energy composite input.
$deltaKEL_{it}$ is the share of the capital-energy-labour composite input.
$deltaL_{it}$ is the share of the labour input.
$deltaND_{it}$ is the share of the intermediate input of the i-th sector.
$deltapetr_{it}$ is the share of the petroleum composite input.
$deltapetrp_{it}$ is the share of the processed petroleum composite input.
$deltapg_{it}$ is the share of the petroleum-gas composite input.
$deltapow_{it}$ is the share of the electricity-heat composite input.
E_{it} is the energy composite input.
$Ecoal_{it}$ is the coal composite input.
$Eelec_{it}$ is the electricity composite input.
$Efipow_{it}$ is the heat input.
$Efos_{it}$ is the fossil composite input.
$EFuel1_{it}$ is the coal mining input.
$EFuel2_{it}$ is the charcoal input.
$EFuel3_{it}$ is the crude oil input.
$EFuel4_{it}$ is the kerosene input.
$EFuel5_{it}$ is the gasoline input.
$EFuel5\_6\_7_{it}$ is the gasoline-diesel-fuel-oil composite input.
$EFuel6_{it}$ is the diesel oil input.
$EFuel6\_7_{it}$ is the diesel-fuel-oil composite input.
$EFuel7_{it}$ is the fuel oil input.
$EFuel8_{it}$ is the gas composite input.
$Egasm_{it}$ is the gas input.
$Egasn_{it}$ is the natural gas input.
$Epetr_{it}$ is the petroleum composite input.
$Epetrp_{it}$ is the processed petroleum composite input.
Epg_{it} is the petroleum-gas composite input.
$Epow_{it}$ is the electricity-heat composite input.
K_{it} is the capital input.
KE_{it} is the capital-energy composite input.
KEL_{it} is the capital-energy-labour composite input.
L_{it} is the labour input.
ND_{it} is the intermediate input of the i-th sector.
PE_{it} is the price of the energy composite input.

$PEcoal_{it}$ is the price of the coal composite input.
$PEelec_{it}$ is the price of the electricity composite input.
$PEfipow_{it}$ is the price of the heat input.
$PEfos_{it}$ is the price of the fossil composite input.
$PEFuel1_{it}$ is the price of the coal mining input.
$PEFuel2_{it}$ is the price of the charcoal input.
$PEFuel3_{it}$ is the price of the crude oil input.
$PEFuel4_{it}$ is the price of the kerosene input.
$PEFuel5_{it}$ is the price of the gasoline input.
$PEFuel5\_6\_7_{it}$ is the price of the gasoline-diesel-fuel-oil composite input.
$PEFuel6_{it}$ is the price of the price of the diesel oil input.
$PEFuel6\_7_{it}$ is the price of the diesel-fuel-oil composite input.
$PEFuel7_{it}$ is the price of the fuel oil input.
$PEFuel8_{it}$ is the price of the gas composite input.
$PEgasm_{it}$ is the price of the gas input.
$PEgasn_{it}$ is the price of the natural gas input.
$PEpetr_{it}$ is the price of the petroleum composite input.
$PEpetrp_{it}$ is the price of the processed petroleum composite input.
$PEpg_{it}$ is the price of the petroleum-gas composite input.
$PEpow_{it}$ is the price of the electricity-heat composite input.
PK_{it} is the price of the capital factor input.
PKE_{it} is the price of the capital-energy composite input.
$PKEL_{it}$ is the price of the capital-energy-labour composite input.
$PND_{oths,it}$ is the price of the unit intermediate input.
PQ_{it} is the price of an Armington composite good.
PX_{it} is the price of the output of the i-th sector.
QX_{it} is the output of the i-th sector.
tc_{it} is the carbon tax imposed on the output of an energy sector.
$UND_{oths,it}$ is the unit intermediate input.
WK_t is the price of the capital input.
WL_t is the price of the labour input
$wldist_{it}$ is the sectoral unit labour input.
$wrdist_{it}$ is the sectoral unit capital input.
$parQX_{it}$, $parKEL_{it}$, $parKE_{it}$, $parE_{it}$, $parPG_{it}$, $parcoal_{it}$, $pargas_{it}$, $parpetr_{it}$, and $parpow_{it}$ are all the elasticity parameters in the CES functions.
$scaleKEL_{it}$ and $scaleKE_{it}$ are the scale parameters in the CES functions.
****************************Electricity Production Function**************************

$EFuel9_{it} = deltaFuel9_{it}^{\frac{1}{1-parpow_{it}}} \times \frac{PEelec_t}{PQ_{"TD",t}\times(1+tc_{"TD",t})}^{\frac{1}{1-parpow_{it}}} \times Eelec_{it};$

$Eelecgen_{it} = deltaelecgen_{it}^{\frac{1}{1-parpow_{it}}} \times (\frac{PEelec_t}{PEelecgen_t})^{\frac{1}{1-parpow_{it}}} \times Eelec_{it};$

$Eelec_{it} = (deltaFuel9_{it} \times EFuel9_{it}^{parpow_{it}} + deltaelecgen_{it} \times Eelecgen_{it}^{parpow_{it}})^{1/parpow_{it}};$

$Efosgen_{it} = deltafosgen_{it}^{\frac{1}{1-parpow_{it}}} \times (\frac{PEelecgen_t}{PEfosgen_t})^{\frac{1}{1-parpow_{it}}} \times Eelecgen_{it};$

$Erenewgen_{it} = deltarenewgen_{it}^{\frac{1}{1-parpow_{it}}} \times (\frac{PEelecgen_t}{PErenewgen_t})^{\frac{1}{1-parpow_{it}}} \times Eelecgen_{it};$

$Eelecgen_{it} = (deltafosgen_{it} \times Efosgen_{it}^{parpow_{it}} + deltarenewgen_{it} \times$
$Erenewgen_{it}^{parpow_{it}})^{1/parpow_{it}};$

$Ecoalgen_{it} = deltacoalgen_{it}^{\frac{1}{1-parpow_{it}}} \times (\frac{PEfosgen_t}{PEcoalgen_t})^{\frac{1}{1-parpow_{it}}} \times Efosgen_{it};$

$EFuel13_{it} = deltaFuel13_{it}^{\frac{1}{1-parpow_{it}}} \times \frac{PEfosgen_t}{PQ_{"NG",t}\times(1+tc_{"NG",t})}^{\frac{1}{1-parpow_{it}}} \times Efosgen_{it};$

$Efosgen_{it} = (deltacoalgen_{it} \times Ecoalgen_{it}{}^{parpow_{it}} + deltaFuel13_{it} \times EFuel13_{it}{}^{parpow_{it}})^{1/parpow_{it}}$;

$EFuel10_{it} = deltaFuel10_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEcoalgen_t}{PQ_{"\mathrm{Supercrit}",t} \times (1+tc_{"\mathrm{Supercrit}",t})}^{\frac{1}{1-parpow_{it}}} \times Ecoalgen_{it}$;

$EFuel11\_12_{it} = deltaFuel11\_12_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEcoalgen_t}{PEFuel11\_12_{it}}^{\frac{1}{1-parpow_{it}}} \times Ecoalgen_{it}$;

$Ecoalgen_{it} = (deltaFuel10_{it} \times EFuel10_{it}{}^{parpow_{it}} + deltaFuel11\_12_{it} \times EFuel11\_12_{it}{}^{parpow_{it}})^{1/parpow_{it}}$;

$EFuel11_{it} = deltaFuel11_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel11\_12_{it}}{PQ_{"\mathrm{USC}",t} \times (1+tc_{"\mathrm{USC}",t})}^{\frac{1}{1-parpow_{it}}} \times EFuel11\_12_{it}$;

$EFuel12_{it} = deltaFuel12_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel11\_12_{it}}{PQ_{"\mathrm{subc}",t} \times (1+tc_{"\mathrm{subc}",t})}^{\frac{1}{1-parpow_{it}}} \times EFuel11\_12_{it}$;

$EFuel11\_12_{it} = (deltaFuel11_{it} \times EFuel11_{it}{}^{parpow_{it}} + deltaFuel12_{it} \times EFuel12_{it}{}^{parpow_{it}})^{1/parpow_{it}}$;

$EFuel14_{it} = deltaFuel14_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PErenewgen_t}{PQ_{"\mathrm{Nuclear}",t} \times (1+tc_{"\mathrm{Nuclear}",t})}^{\frac{1}{1-parpow_{it}}} \times Erenewgen_t$;

$EFuel15\_16\_17_{it} = deltaFuel15\_16\_17_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PErenewgen_t}{PEFuel15\_16\_17_{it}}^{\frac{1}{1-parpow_{it}}} \times Erenewgen_t$;

$Erenewgen_t = (deltaFuel14_{it} \times EFuel14_{it}{}^{parpow_{it}} + deltaFuel15\_16\_17_{it} \times EFuel15\_16\_17_{it}{}^{parpow_{it}})^{1/parpow_{it}}$;

$EFuel15_{it} = deltaFuel15_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel15\_16\_17_{it}}{PQ_{"\mathrm{Hydro}",t} \times (1+tc_{"\mathrm{Hydro}",t})}^{\frac{1}{1-parpow_{it}}} \times EFuel15\_16\_17_{it}$;

$EFuel16\_17_{it} = deltaFuel16\_17_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel15\_16\_17_{it}}{PEFuel16\_17_{it}}^{\frac{1}{1-parpow_{it}}} \times EFuel15\_16\_17_{it}$;

$EFuel15\_16\_17_{it} = (deltaFuel15_{it} \times EFuel15_{it}{}^{parpow_{it}} + deltaFuel16\_17_{it} \times EFuel16\_17_{it}{}^{parpow_{it}})^{1/parpow_{it}}$;

$EFuel16_{it} = deltaFuel16_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel16\_17_{it}}{PQ_{"\mathrm{wind}",t} \times (1+tc_{"\mathrm{wind}",t})}^{\frac{1}{1-parpow_{it}}} \times EFuel16\_17_{it}$;

$EFuel17_{it} = deltaFuel17_{it}{}^{\frac{1}{1-parpow_{it}}} \times \frac{PEFuel16\_17_{it}}{PQ_{"\mathrm{solarpv}",t} \times (1+tc_{"\mathrm{solarpv}",t})}^{\frac{1}{1-parpow_{it}}} \times EFuel16\_17_{it}$;

$EFuel16\_17_{it} = (deltaFuel16_{it} \times EFuel16_{it}{}^{parpow_{it}} + deltaFuel17_{it} \times EFuel17_{it}{}^{parpow_{it}})^{1/parpow_{it}}$.

$deltacoalgen_{it}$ is the share of the coal electricity composite input.
$deltaelecgen_{it}$ is the share of the electricity-generation composite input;
$deltafosgen_{it}$ is the share of the fossil electricity input.
$deltaFuel9_{it}$ is the share of the electricity transmission input.
$deltaFuel10_{it}$ is the share of the supercrit-coal electricity input.
$deltaFuel11_{it}$ is the share of the USC-coal electricity input.
$deltaFuel11\_12_{it}$ is the share of the USC-subc-coal electricity composite input.
$deltaFuel12_{it}$ is the share of the subc-coal electricity input.
$deltaFuel13_{it}$ is the share of the gas electricity input.
$deltaFuel14_{it}$ is the share of the nuclear electricity input.
$deltaFuel15_{it}$ is the share of the hydroelectricity input.
$deltaFuel15\_16\_17_{it}$ is the share of the hydro-wind-solar electricity composite input.
$deltaFuel16_{it}$ is the share of the wind electricity input.
$deltaFuel16\_17_{it}$ is the share of the wind-solar electricity composite input.
$deltaFuel17_{it}$ is the share of the solar electricity input.
$deltarenewgen_{it}$ is the share of the renewable electricity generation input.
$Ecoalgen_{it}$ is the coal electricity composite input.
$Eelecgen_{it}$ is the electricity-generation composite input;

$Efosgen_{it}$ is the fossil electricity input.
$EFuel9_{it}$ is the electricity transmission input.
$EFuel10_{it}$ is the supercrit-coal electricity input.
$EFuel11_{it}$ is the USC-coal electricity input.
$EFuel11\_12_{it}$ is the USC-subc-coal electricity composite input.
$EFuel12_{it}$ is the subc-coal electricity input.
$EFuel13_{it}$ is the gas electricity input.
$EFuel14_{it}$ is the nuclear electricity input.
$EFuel15_{it}$ is the hydroelectricity input.
$EFuel15\_16\_17_{it}$ is the hydro-wind-solar electricity composite input.
$EFuel16_{it}$ is the wind electricity input.
$EFuel16\_17_{it}$ is the wind-solar electricity composite input.
$EFuel17_{it}$ is the solar electricity input.
$Erenewgen_{it}$ is the renewable electricity generation input.
$PEcoalgen_{it}$ is the price of the coal electricity composite input.
$PEelecgen_{it}$ is the price of the electricity-generation composite input;
$PEfosgen_{it}$ is the price of the fossil electricity input.
$PEFuel9_{it}$ is the price of the electricity transmission input.
$PEFuel10_{it}$ is the price of the supercrit-coal electricity input.
$PEFuel11_{it}$ is the price of the USC-coal electricity input.
$PEFuel11\_12_{it}$ is the price of the USC-subc-coal electricity composite input.
$PEFuel12_{it}$ is the price of the subc-coal electricity input.
$PEFuel13_{it}$ is the price of the gas electricity input.
$PEFuel14_{it}$ is the price of the nuclear electricity input.
$PEFuel15_{it}$ is the price of the hydroelectricity input.
$PEFuel15\_16\_17_{it}$ is the price of the hydro-wind-solar electricity composite input.
$PEFuel16_{it}$ is the the price of wind electricity input.
$PEFuel16\_17_{it}$ is the price of the wind-solar electricity composite input.
$PEFuel17_{it}$ is the price of the solar electricity input.
$PErenewgen_{it}$ is the price of the renewable electricity generation input.
*********************************Trade Function*********************************

$PWM_{it} = PWM0_{it} \times EXR_t;$

$PWE_{it} = PWE0_{it} \times EXR_t;$

$\mathrm{scaleQQ}_i = \frac{QQ0_i}{(deltaQM_i \times QM0_i^{\mathrm{etaQq}_j} + deltaQD_i \times QD0_i^{\mathrm{etaQq}_j})^{\frac{1}{\mathrm{etaQq}_i}}};$

$deltaQM_i = \frac{(1+tm_i) \times QM_i^{1-\mathrm{etaQq}_i}}{QD0_i^{1-\mathrm{etaQq}_i} + (1+tm_i) \times QM_i^{1-etaQq_i}};$

$QD_{it} = (scaleQQ_{it}{}^{etaQq_{it}} \times deltaQD_{it} \times \frac{PQ_{it}}{PD_{it}})^{\frac{1}{1-etaQq_{jt}}} \times QQ_{it};$

$QM_{it} = (scaleQQ_{it}{}^{etaQq_{it}} \times deltaQM_{it} \times \frac{PQ_{jt}}{PWM_{it}(1+tm_{it})})^{\frac{1}{1-etaQq_{it}}} \times QQ_{it};$

$deltaQD_i = 1 - deltaQM_i;$

$QQ0_i = QD0_i + (1 + tm_i) \times QM0_i;$

$QQ_{it} = scaleQQ_{it} \times (deltaQM_{it} \times QM_{it}^{etaQq_{it}} + deltaQD_{it} \times QD_{it}^{etaQq_{it}})^{\frac{1}{\mathrm{etaQq}_{it}}};$

$QD_{mt} = (scaleCET_{mt}{}^{phiCET_{mt}} \times deltaQDs_{mt} \times \frac{(1+tind_{mt}) \times PX_{mt}}{PD_{mt}})^{\frac{1}{1-phiCET_{mt}}} \times QX_{mt};$

$QE_{mt} = (scaleCET_{mt}{}^{phiCET_{mt}} \times deltaQE_{mt} \times \frac{(1+tind_{mt}) \times PX_{mt}}{PWE_{mt}})^{\frac{1}{1-phiCET_{mt}}} \times QX_{mt};$

$QX_{mt} = scaleCET_{mt} \times (deltaQDs_{mt} \times QD_{mt}^{phiCET_{mt}} + deltaQE_{mt} \times QE_{mt}^{phiCET_{mt}})^{1/phiCET_{mt}};$

$QD_{nt} = (1 + tind_{nt}) \times QX_{nt};$

$QE_{nt} = 0;$

$PD_{nt} = PX_{nt};$

$tm_{it} = \frac{TARIFF_{it}}{QM_{it}}$.

Subscript “m” and “n” refers to a traded and nontraded good respectively.
$deltaQD_i$ is the QD share parameter in the Armington function.
$deltaQM_i$ is the QM share parameter in the Armington function.
$etaQq_i$ is the elasticity parameter in the Armington function.
EXR_t is the currency exchange rate.
PD_{it} is the price of the domestic good.
$phiCET_{mt}$ is the elasticity parameter in the CET function.
PQ_{it} is the price of the Armington composite good.
PWE_{it} is the export price.
$PWE0_{it}$ is the baseline export price.
PWM_{it} is the import price.
$PWM0_{it}$ is the baseline import price.
PX_{mt} is the price of the domestic sectoral output.
QD_{it} is the domestic good.
$QD0_{it}$ is the baseline domestic good.
QM_{it} is the import good.
$QM0_{it}$ is the baseline import good.
QQ_{it} is the Armington composite good.
$QQ0_{it}$ is the baseline Armington composite good.
QX_{mt} is the domestic sectoral output.
scaleQQ_i is the scale parameter in the Armington function.
$TARIFF_{it}$ is the tariff.
$tind_{it}$ is the rate of the production tax.
tm_j is the tariff rate.
*********************************Household Function*******************************
$YH_{it} = WL_t \times wldist_{it} \times L_{it}$;
$TYL_t = \sum_i YH_{it}$;
$YHK_t = ratehk_t \times TYK_t$;
$YHW_t = ratehw_t \times \sum_j (PWM_{jt} \times QM_{jt})$;
$YHT_t = TYL_t + YHK_t + YEH_t + YHG_t + YHW_t$;
$SH_t = savh_t \times YHT_t$;
$HDY_t = YHT_t - SH_t - GHTAX_t$;
$LHD_t = \sum_i (LHD0_{it} \times PQ_{it}) + \sum_Q (HDFuel_{Qt} \times PY_{Qt} \times tc_{Qt})$;
$HD_{nfe,t} \times PQ_{nfe,t} = LHD0_{nfe,t} \times PQ_{nfe,t} + mpc_{nfe,t} \times (HDY_t - LHD_t)$;
$HD_{fe,t} \times PQ_{fe,t} \times \left(1 + tc_{fe,t}\right) = LHD0_{fe,t} \times PQ_{fe,t} \times (1 + tc_{fe,t}) + mpc_{fe,t} \times (HDY_t - LHD_t)$.

The subscript Q refers to an energy product; nfe refers to a nonenergy sector; fe refers to an energy sector.
$GHTAX_t$ is the household income tax.
HD_{it} is the household consumption.
$HDFuel_{Qt}$ is the household energy consumption.
HDY_t is the household disposable income.
LHD_t is the minimum household consumption.
$LHD0_{it}$ is the baseline minimum household consumption.
mpc_{it} is the household marginal propensity to consume.
PY_{Qt} is the energy price.
$ratehk_t$ is the rate of household capital income in the capital income.
$ratehw_t$ is the rate of household income from the RW.
$savh_t$ is the rate of household saving.

SH_t is the household saving.
TYK_t is the total income from the capital.
TYL_t is the total household income from the labour.
WL_t is the price of the labour input
$wldist_{it}$ is the sectoral unit labour input.
YEH_t is the household transfer income from the enterprise.
YH_{it} is the sectoral household income from the labour.
YHG_t is the household transfer income from the government.
YHK_t is the household income from the capital.
YHW_t is the household income from the rest of the world (RW).
YHT_t is the total household income.
********************************** Enterprise Function*****************************
$YK_{it} = WK_t \times wrdist_{it} \times K_{it}$;
$TYK_t = \sum_i YK_{it}$;
$YWK_t = ratewk_t \times TYK_t$;
$YEK_t = (1 - ratehk_t - ratewk_t) \times TYK_t$;
$YEH_t = ratehe_t \times YEK_t$;
$SE_t = YEK_t - YEH_t - GETAX_t$;
$STO_{it} = stoinv_{it} \times QX_{it}$.

$ratehe_t$ is the rate of the enterprise income transfer to the household.
$ratewk_t$ is the rate of the RW capital income in the total capital income.
SE_t is the enterprise saving.
STO_{it} is the sectoral stock.
$stoinv_{it}$ is the sectoral rate of the stock in the produced good.
TYK_t is the total capital income.
WK_t is the price of the capital input.
$wrdist_{it}$ is the sectoral unit capital input.
YEK_t is the enterprise capital income.
YK_{it} is the sectoral capital income.
YWK_t is the RW capital income.
********************************** Government Function***************************
$GINDTAX_{it} = tind_{it} \times PX_{it} \times QX_{it}$;
$GTRIFM_{it} = tm_{it} \times PWM_{it} \times QM_{it}$;
$GHTAX_t = th_t \times YHT_t$;
$GETAX_t = te_t \times YEK_t$;
$GWY_t = rategw_t \times \sum_i (PWM_{it} \times QM_{it})$;
$YGT_t = \sum_i GINDTAX_{it} + \sum_i GTRIFM_{it} + GHTAX_t + GETAX_t + GWY_t + TCTAX_t$;
$YHG_t = ratehg_t \times YGT_t$;
$YWG_t = ratewg_t \times YGT_t$;
$SG_t = savg_t \times YGT_t$;
$GD_{nfe,t} = cong_{nfe,t} \times (1 - ratehg_t - ratewg_t - savg_t) \times YGT_t / PQ_{nfe,t}$;
$(1 + tc_{fe,t}) \times GD_{fe,t} = cong_{fe,t} \times (1 - ratehg_t - ratewg_t - savg_t) \times YGT_t / PQ_{fe,t}$.

$cong_{fe,t}$ is the rate of government consumption.
GD_{it} is the government consumption.
$GINDTAX_{it}$ is the sectoral production tax.
$GTRIFM_{it}$ is the import tax.
GWY_t is the government income from the RW.
$ratehg_t$ is the rate of government transfer to the household in the government income.
$rategw_t$ is the rate of the RW transfer to the government in the RW income.

$savg_t$ is the government saving rate.
SG_t is the government saving.
$TCTAX_t$ is the carbon tax revenues.
te_t is the rate of the enterprise income which is taxed.
th_t is rate of the household income which is taxed.
$tind_{it}$ is rate of the production tax in the monetary value of the produced good.
tm_{it} is the rate of the import good which is taxed.
YGT_t is the total government income.
YHG_t is the government money transfer to the household.
YWG_t is the government money transfer to the RW.
*****************************Equilibrium Function*********************************
$\sum_i(PWM_{it} \times QM_{it}) + YWK_t + YWG_t = \sum_i(PWE_{it} \times QE_{it}) + YHW_t + GWY_t + SF_t \times EXR_t;$
$TSAV_t = SE_t + SG_t + SH_t + SF_t \times EXR_t;$
$TINV_t = TSAV_t - \sum_{nfe}(STO_{nfe,t} \times PQ_{nfe,t}) - \sum_{nfe}[STO_{nfe,t} \times PQ_{nfe,t} \times (1 + tc_{fe,t})];$
$INV_{nfe,t} = invest_{nfe,t} \times TINV_t/PQ_{nfe,t};$
$INV_{fe,t} \times (1 + tc_{fe,t}) = invest_{fe,t} \times TINV_t/PQ_{fe,t};$
$\sum_i K_{it} = KS0_t;$
$\sum_i L_{it} = LS0_t;$
$SGDP_{it} = YH_{it} + YK_{it} + GINDTAX_{it};$
$RGDP_t = \sum_i SGDP_{it};$
$GDP_t = RGDP_t \times PGDP_t.$

GDP_t is the Chinese GDP.
INV_{it} is the sectoral investment.
$invest_{it}$ is the rate of the investment on Sector i in the total investment.
$KS0_t$ is the baseline total capital supply.
$LS0_t$ is the baseline total labour supply.
$PGDP_t$ is the GDP deflator.
$RGDP_t$ is the real GDP in China.
SF_t is the RW saving.
$SGDP_{it}$ is the sectoral output.
$TINV_t$ is the total investment.
$TSAV_t$ is the total saving.
*****************************Carbon Emission Function******************************
$PY_{Qt} = PY0_{Qt} \times PGDP_t/PGDP0_t;$
$SFuel_{iQt} = SFuel0_{iQt} \times (SGDP_{it}/PGDP_t)/(SGDP0_{it}/PGDP0_t);$
$SCE_{it} = \sum_Q(SFuel0_{iQt} \times cef_Q);$
$HDFuel_{Qt} = HDFuel0_{Qt} \times \sum_i(HD_{it} \times PQ_{it})/\sum_i(HD0_{it} \times PQ0_{it});$
$HCE_t = \sum_Q(HDFuel_{Qt} \times cef_Q);$
$TCE_t = \sum_i SCE_{it} + HCE_t;$
$CI_t = TCE_t/RGDP_t.$

cef_Q is the carbon emission factor.
CI_t is the carbon intensity.
HCE_t is the household carbon emissions.
$HDFuel_{Qt}$ is the household energy consumption.
$HDFuel0_{Qt}$ is the baseline household energy consumption.
PY_{Qt} is the energy price.
$PY0_{Qt}$ is the baseline energy price.
SCE_{it} is the sectoral carbon emissions.

$SFuel_{iQt}$ is the sectoral energy consumption.
$SFuel0_{iQt}$ is the baseline energy consumption.
TCE_t is the total carbon emissions.
*******************************Carbon Tax Function********************************
$ETAX_{fe,t} = tc_{fe,t} \times (YH_{fe,t} + YK_{fe,t} + GINDTAX_{fe,t})$;
$TCTAX_t = \sum_{fe} ETAX_{fe,t}$.

$ETAX_{fe,t}$ is the carbon tax imposed on the output of an energy sector.
$TCTAX_t$ is the total carbon tax.
*********************************Welfare Function*********************************
$EV_t = \sum_i (PQ0_{it} \times HD_{it}) - \sum_i (PQ0_{it} \times HD0_{it})$.

EV_t is the welfare change induced from the equivalent variation.

Appendix C: Dynamic Transitions

Demographic Changes

There are no official projections of the Chinese population by the Chinese government, but UN (2017) have projected the Chinese population in nine scenarios in 2017 World Population Prospects (WPP).

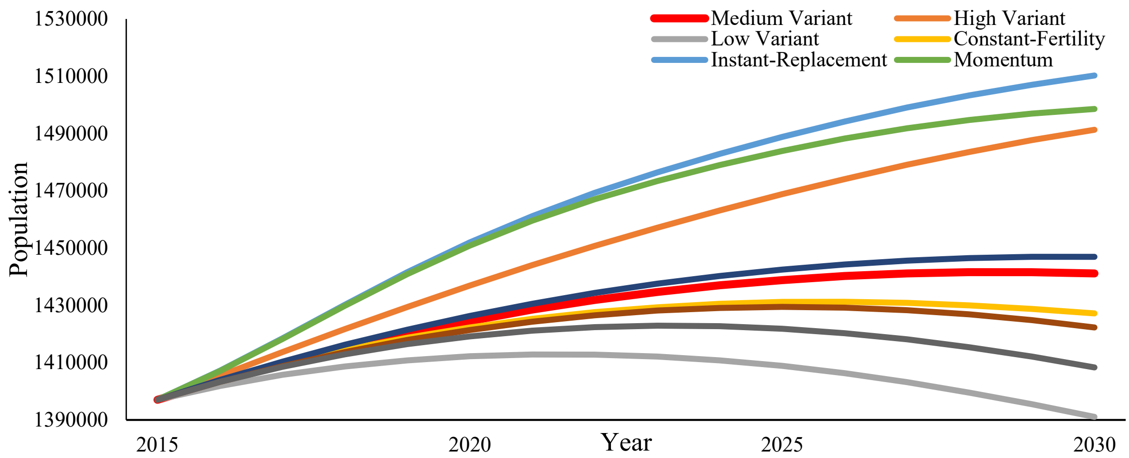


Fig. C1 The Projected Chinese Population in 2016–2030 (Unit: thousands)

Table C1 The Projected Chinese Population in the Medium Variant Scenario (Unit: thousands)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Population	1397029	1403500	1409517	1415046	1420062	1424548	1428481	1431850
Year	2023	2024	2025	2026	2027	2028	2029	2030
Population	1434676	1436995	1438836	1440205	1441106	1441555	1441574	1441182

Source: UN (2017)

Fig. C1 shows that in all scenarios except the high variant scenario, the Chinese population will rise slowly or even decline in 2030. This projection is consistent with Cai (2012) who empirically found that the growth rate of the Chinese population will gradually diminish to zero, and the peak time will be 2030. The projected curve of the medium variant scenario is highlighted in red as it is in the middle of the nine curves. Hence, the Chinese population is assumed to follow the curve of the medium variant scenario, where the Chinese population will have a medium variation of fertility rate. Table C1 shows the population data of the medium variant scenario. According to Table C1, the Chinese population is expected to peak in 2029, and the annual population growth rate will become negative in 2030.

Low fertility rate induced by family planning policies may result in the shrinking labour force. In the literature, many researchers argued that China has already reached the Lewis turning point (Cai 2010, Zhang, Yang et al. 2011) where labour supply becomes in shortage, and it is no longer unlimited (Cai 2010). Population projection with a total fertility rate (TFR) of 1.4 indicated that the percentage of working-age population peaked in 2013 at 71.9% and will be 67.5% in 2030 (Du and Yang 2014). According to 2017 China Statistical Yearbook, the number of population aged 15–64 peaked in 2013, and it has declined since then. By comparison, the total population remains to grow slightly with the growth mainly from people aged 65 and over. Hence, China's labour force will continue to decline even if the government has already revised the family planning policy from one-child to two-child policy (Wang, Zhao et al. 2017).

High dependency ratio is another demographic phenomenon that may arouse great concern in the future. According to 2017 WPP, the dependency ratio (ratio of dependent population per working-age population) of China will be 48.0% in 2030, 67.4% in 2050, and 83.8% in 2100 in the medium variant scenario (UN 2017). The increasing dependency ratio is due to the decrease of the working-age population and the increase of dependent population.

Table C2 Working Age and Dependent Population in China (Unit: thousands)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Working-age	1014777	1012998	1010367	1007330	1004476	1002172	1000769	999793
Dependent	382251	390502	399150	407716	415586	422376	427712	432056
Year	2023	2024	2025	2026	2027	2028	2029	2030
Working-age	998932	997678	995649	992809	989409	985258	980050	973598
Dependent	435744	439317	443186	447396	451697	456297	461524	467584

Source: UN (2017)

Table C2 shows the projected working-age and dependent population in the medium variant scenario by 2017 WPP. As there are no official projections of the Chinese population in age groups, I assume that the historical population data from the Chinese government will change proportionally to the WPP data. Although 2017 WPP includes the historical population data, I have used the data from the Chinese government for the consistency purpose as the database of the CGE model is based on the statistical yearbooks published by the Chinese authorities. Noticeably, the working-age population is assumed to be inputted as a production factor with full employment. Eq. (1) are the equations showing the growth of population and labour respectively.

$$\begin{cases} N_{t+1} = N_t * \frac{N_{t+1}^*}{N_t^*} = N_0 * \frac{N_{t+1}^*}{N_0^*} \\ L_{i,t+1} = L_{it} * \frac{L_{t+1}^*}{L_t^*} = L_{i0} * \frac{L_{t+1}^*}{L_0^*} \end{cases} \tag{C1}$$

In Eq. (C1), the subscript i refers to an industrial sector, and the subscript 0 denotes the base year 2015. N_t is the total population in Year t; L_{it} is the number of employees in Sector i in Year t. N_t^* is the total population in Year t published by WPP; L_t^* is the working-age population in Year t published by WPP. Because there are no sectoral working age population in 2017 WPP, I assume that the sectoral data in the CGE model will follow the same trend as the total data in 2017 WPP.

Economic Change

The Organisation for Economic Co-operation and Development (OECD) has published regional GDP long-term forecast, whilst other organisations, such as the World Bank and United Nations, only provided regional GDP short-term forecast. Based on OECD (2018), Fig. C2 shows the forecast GDP growth rate in China during 2016–2020. Noticeably, the GDP projection is based on the 2015 GDP, whose data is from 2015 China Input-Output Table.

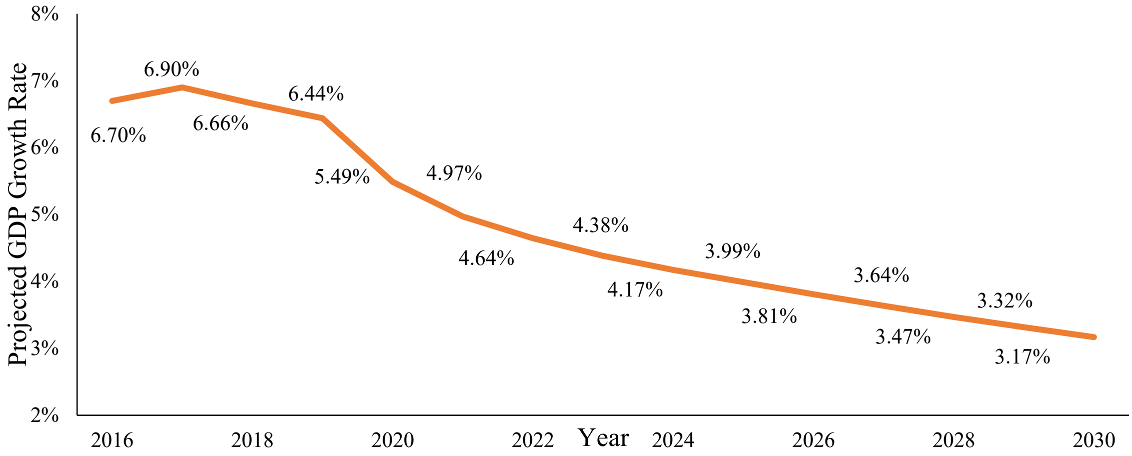


Fig. C2 Projected GDP Growth Rate in China

According to Fig. C2, the GDP growth rate will decline continuously since 2017, and the number in 2030 will be less than half of the number in 2017. Sectoral output growth may follow a different growth route from the national GDP. Nevertheless, owing to the lack of data, I assume that the projected gross output and intermediate use of nonenergy sectors will follow the GDP projection by OECD (2018) and labour projection in 2017 WPP, shown in Eq. (C2) and (C3) respectively. The subscript ne refers to a nonenergy sector; $SGDP_{ne,t}$ is the sectoral output of Sector ne in Year t; GDP_t^* is the projected GDP in Year t by OECD (2018); $IMU_{ne,jt}$ is the input of Commodity j in the output of Sector ne in Year t; L_t is the total employed labour in Year t.

$$SGDP_{ne,t} = SGDP_{ne,t-1} \times \frac{GDP_t^*}{GDP_{t-1}^*} \times \frac{L_t}{L_{t-1}} = SGDP_{ne,0} \times \frac{GDP_t^*}{GDP_0^*} \times \frac{L_t}{L_0} \tag{C2}$$

$$IMU_{ne,jt} = IMU_{ne,j,t-1} \times \frac{GDP_t^*}{GDP_{t-1}^*} \times \frac{L_t}{L_{t-1}} = IMU_{ne,j0} \times \frac{GDP_t^*}{GDP_0^*} \times \frac{L_t}{L_0} \tag{C3}$$

Inflation usually occurs with the economic growth. Like GDP data, to my best knowledge, OECD is the only major international organisation that has recently published long-term projections of price levels around the world. In the OECD database, Archive 2014 is the most recent publication that includes long term baseline projections. The projected price change in 2016–2030 is shown in Fig. C3. Noticeably, the price projection is based on the base year 2015 price which is set to one. This is because the CGE model analyses how relative price changes affect the model equilibrium.

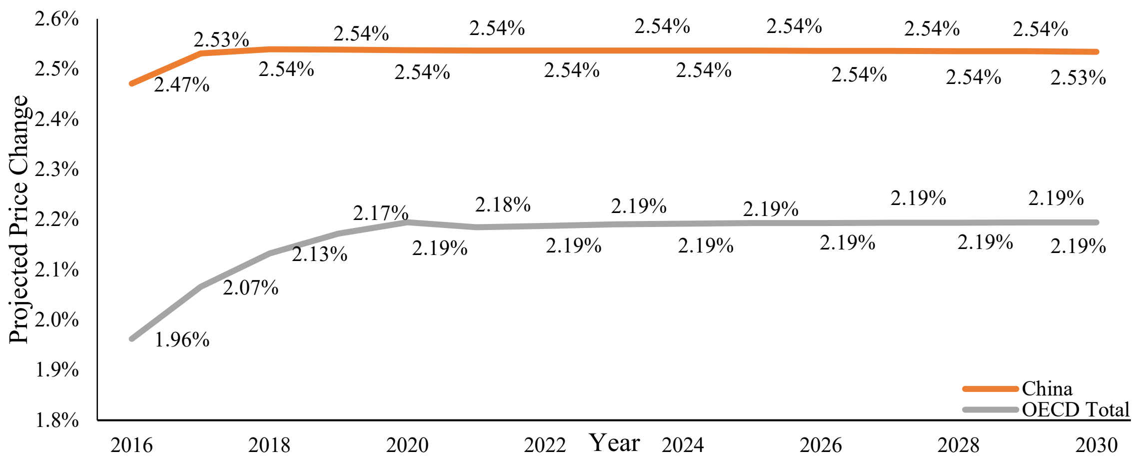


Fig. C3 Projected Annual Price Growth in China and OECD (Countries) Total

Fig. C3 shows the projected price growth in China and total OECD countries. The price growth in China will be higher than that in OECD total. The curve for China is expected to become stable in 2017, while the curve for OECD total will be stable since 2019. The prices of domestic goods, intermediate inputs, production factors are assumed to follow the curve for China in Fig. C3. As the world GDP deflator data is not available in OECD (2014), I assume that the projected price changes of import and export goods in China will follow the curve for OECD Total in Fig. C3.

Energy Consumption

Table C3 Emission Factors and Densities of Fossil Fuels

	Emission Factor	Unit	Density	Unit
Coal	1.9804	$kg(CO_2)/kg$		
Charcoal	3.1839	$kg(CO_2)/kg$		
Crude Oil	3.0703	$kg(CO_2)/L$	0.846	kg/L
Kerosene	3.0992	$kg(CO_2)/L$	0.79	kg/L
Gasoline	3.1941	$kg(CO_2)/L$	0.744	kg/L
Diesel Oil	3.1630	$kg(CO_2)/L$	0.836	kg/L
Fuel Oil	3.2392	$kg(CO_2)/L$	0.89	kg/L
Natural Gas	1.9976	$kg(CO_2)/m^3$		
Electricity	0	$kg(CO_2)/kwh$		

Source: IPCC (2006)

Table C3 shows the emission factors of fossil fuels calculated basing on IPCC (2006). For the sake of unit conformity, the emissions of the liquid energies need to be divided by the corresponding density. The emission factor of electricity is assumed to be zero as the consumption of electricity generates very few emissions compared to the overall anthropogenic emissions. The 2015 sectoral carbon emissions are calculated basing on the emission factors in Table C3 and sectoral energy consumption data in China Energy Statistical Yearbook. By comparison, the sectoral carbon emissions in 2016–2030 are calculated basing on the assumption of sectoral energy consumption growth shown below.

According to the report of CNPC Economics &Technology Research Institute (ETRI), China's oil demand will experience an annual increase of 2.7% in 2015–2020, 1.2% in 2020–2030, and it will peak in 2030. The demand for natural gas will increase by 8.1% annually during 2015–2030; in contrast, the demand for coal will decrease by 1.1% yearly in the meantime (ETRI 2017). I assume that energy demand equals energy consumption.

$$oil_t = \begin{cases} oil_0(1+2.7\%)^{t-2016}, 2016 < t \leq 2020 \\ oil_0(1+2.7\%)^4 * (1+1.2\%)^{t-2020}, 2020 < t \leq 2030 \end{cases} \tag{C4}$$

$$gas_t = gas_0 * (1+8.1\%)^{t-2016}, 2016 < t \leq 2030 \tag{C5}$$

$$coal_t = coal_0 * (1-1.1\%)^{t-2016}, 2016 < t \leq 2030 \tag{C6}$$

In Eq. (C4) to (C6), oil_t, gas_t, and $coal_t$ refer to the oil, gas, and coal consumption in Year t respectively. According to the ETRI report, the increase of oil consumption is mainly driven by the transport sector, and the drop of increase rate in 2020 is caused by the peaking of household, commercial and industrial consumption. Electricity generation and industrial and household use will induce the increase of gas consumption, because the Chinese government is implementing “change coal into gas” policy to cope with haze. The decrease of the coal consumption is mainly caused by the falling demand of industrial sectors owing to the structural optimisation and adjustment of the energy consumption. The construction sector will also have a decreasing demand for coal because of the advancement in electric technology.

To compare the projected energy consumption basing on the ETRI report with the data in US Energy Information Administration (EIA), the conversion factors in Table C4 are used.

Table C4 Energy Consumption in British Thermal Unit (Btu)

Energy	Energy Consumption	Unit	Density		Conversion Factor 1	Unit	Conversion Factor 2	Unit	Energy Consumption	Unit
Coal	3970.14	Million Tonnes			907.185	kg/short-ton	19490000	Btu/short-ton	85.29	Quadillion Btu
Charcoal	440.59	Million Tonnes			907.185	kg/short-ton	28690000	Btu/short-ton	13.93	Quadillion Btu
Crude Oil	540.88	Million Tonnes	0.846	kg/L	158.987	L/barrel (US)	5719000	Btu/barrel	23.00	Quadillion Btu
Kerosene	26.64	Million Tonnes	0.79	kg/L	158.987	L/barrel (US)	5670000	Btu/barrel	1.20	Quadillion Btu
Gasoline	113.68	Million Tonnes	0.744	kg/L	158.987	L/barrel (US)	5057000	Btu/barrel	4.86	Quadillion Btu
Diesel Oil	173.60	Million Tonnes	0.836	kg/L	158.987	L/barrel (US)	5778000	Btu/barrel	7.55	Quadillion Btu
Fuel Oil	46.62	Million Tonnes	0.89	kg/L	158.987	L/barrel (US)	6287000	Btu/barrel	2.07	Quadillion Btu
Natural Gas	193175	Million M^3			0.0283	M^3/cubic foot	1031	Btu/cubic foot	7.03	Quadillion Btu
Sum									144.94	Quadillion Btu

Source: Conversion Factor 1 from Cook (1991)
Conversion Factor 2 from EIA (2016)

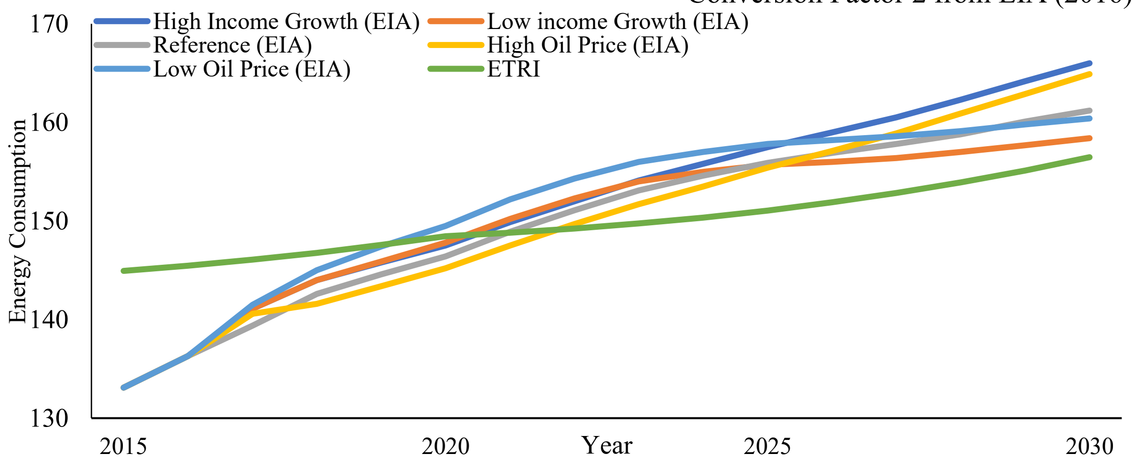


Fig. C4 The Comparison of Projected Energy Consumption in China (Unit: Quadrillion Btu)

Fig. C4 shows the projected total energy consumption basing on the ETRI report in comparison with five scenarios by EIA (2017). According to Fig. C4, the ETRI report overestimated China's energy consumption in 2015–2017 but will underestimate the consumption in 2018–2030. The curve for the reference scenario in EIA (2017) will lie in the middle of the curves, which implies that the reference scenario shows the projected energy consumption in China on average. Hence, in this thesis, the energy consumption growth rate (shown in Table C5) in the reference scenario in EIA (2017) is adopted to calculate the projected energy consumption in 2016–2030 basing on the 2015 sectoral energy consumption data from China Energy Statistical Yearbook. This is because EIA (2017) did not provide sectoral energy consumption data.

Table C5 Projected Energy Consumption Growth Rate

Year	2016	2017	2018	2019	2020	2021	2022	2023
Coal	0.12%	1.05%	-0.46%	-0.58%	-0.82%	0.00%	0.00%	0.00%
Natural Gas	4.35%	5.56%	6.58%	6.17%	3.49%	7.87%	7.29%	6.80%
Petrol	3.31%	3.20%	2.33%	2.27%	2.22%	2.90%	2.82%	2.05%
Electricity	3.00%	2.91%	3.60%	2.48%	1.94%	2.38%	1.62%	1.83%
Manufacturing	0.73%	1.28%	1.08%	0.18%	-0.18%	0.53%	0.53%	0.35%
Year	2024	2025	2026	2027	2028	2029	2030	
Coal	-0.71%	-0.83%	-0.96%	-0.72%	-0.73%	-0.74%	-0.74%	
Natural Gas	4.55%	4.35%	3.33%	4.03%	4.65%	4.44%	4.26%	
Petrol	2.01%	1.97%	1.29%	1.27%	1.26%	0.62%	1.23%	
Electricity	1.35%	1.33%	1.31%	1.08%	1.07%	1.48%	1.46%	
Manufacturing	0.00%	-0.35%	-0.70%	-0.53%	-0.36%	-0.36%	-0.18%	

Source: EIA (2017)

In Table C5, the electricity data means the end use of electricity, and the projected electricity consumption is assumed to have the same growth path as the end use of electricity. According to 1997 China IO Table, the heat sector mainly produces steam and hot water. Because there is no energy consumption projection of the heat sector, the growth of the heat sector is assumed to follow the same pattern as the manufacturing sector in EIA (2017).

The output and intermediate use of an energy sector is assumed to follow the projected energy consumption in EIA (2017) and labour growth in 2017 WPP, shown in C7 and C8 respectively. The subscript e refers to an energy sector consisting of the production or extraction of coal (coal and coke), oil (crude oil and petroleum), gas (gas and natural gas), electricity and heat. EC_{et}^{*} is the energy consumption of Sector e in Year t projected by EIA (2017).

$$SGDP_{e,t+1} = SGDP_{et} \times \frac{EC_{e,t+1}^{*}}{EC_{et}^{*}} \times \frac{L_{t+1}}{L_t} = SGDP_{e0} \times \frac{EC_{e,t+1}^{*}}{EC_{e0}^{*}} \times \frac{L_{t+1}}{L_0} \quad \text{(C7)}$$

$$IMU_{ej,t+1} = IMU_{ejt} \times \frac{EC_{e,t+1}^{*}}{EC_{et}^{*}} \times \frac{L_{t+1}}{L_t} = IMU_{e,j0} \times \frac{EC_{e,t+1}^{*}}{EC_{e0}^{*}} \times \frac{L_{t+1}}{L_0} \quad \text{(C8)}$$

Capital Accumulation

Both physical and human capital can induce technological advancement and thus may affect emissions (Liu, Guo et al. 2017). However, significant differences exist in how physical or human capital affects emissions. Despite its significant role in booming economic growth (Du, Wang et al. 2014), an increase in physical capital will lead to further use of energy and resources, which implies that higher physical capital intensity may cause more pollution (Shimamoto 2017). On the contrary, an increase in human capital may decrease the use of fossil fuels in the production process and thus reduce anthropogenic emissions (Bano, Zhao et al. 2018). This is because human capital may provide the potential minds to understand the energy security and environmental issues, and the knowledge or skills to develop renewable energies (Bano, Zhao et al. 2018). In conclusion, physical capital accumulation may positively affect emissions, whilst human capital accumulation may affect emissions in the opposite direction.

Having not been officially published, the Chinese social capital stock data have to be obtained from the previous research. Long and Herrera (2016) proposed original time series for various definitions of physical capital stock in China in 1952–2014. In this thesis, the projected physical capital stock is based on Long and Herrera (2016), shown in Eq. (C9).

$$PC_{t+1} = PC_t \times (1 - deptPC) + \frac{INVPC_t}{P_t^{GCF}} \tag{C9}$$

In Eq. (C9), PC_t is the capital stock in Year t; $INVPC_t$ is the gross capital formation in Year t; P_t^{GCF} is the price of gross capital formation; $deptPC$ is the capital depreciation rate, which is time-invariant. The 2014 capital stock in Long and Herrera (2016) was based on 1952 price level, and thus it needs to be transformed into the stock at 2015 price level. Because Long and Herrera (2016) only showed the P_t^{GCF} in 1952–2014, I assume that the P_t^{GCF} in 2015–2030 will change proportionally to the GDP deflator projected by OECD (2014). The projected gross capital formation data are also from OECD (2014), but the unit of OECD data needs to be transformed into $yuan$ assuming that the exchange rate in 2016–2030 will remain at the 2015 level. Long and Herrera (2016) shows that the annual depreciation rate of physical capital is 6.68% in 1952–2014, I assume that the depreciation rate in 2015–2030 will remain unchanged.

Table C6 The Projected Physical Capital Stock in China (Unit: constant 2015 trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Stock	197.38	215.71	233.18	250.07	266.03	281.33	296.02	310.13
Year	2023	2024	2025	2026	2027	2028	2029	2030
Stock	323.51	336.41	348.69	360.44	371.73	382.64	393.26	403.71

Table C6 shows the projected Chinese physical capital stock calculated using Eq. (C8). According to Table C6, the physical capital stock will increase steadily over the studied period; however, the growth rate will gradually decrease.

Human capital is defined as the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being (Li, Liang et al. 2013). Compared to physical capital stock, human capital stock is even more difficult to measure. Hence, very few studies have successfully measured the Chinese human capital stock, considering the enormous amount of the time and effort required for data collection, parameter estimation, and computation (Li, Liang et al. 2013). China Centre for Human Capital and Labour Market Research (CHLR) has undertaken an expansive research project to study the human capital in China since 2008. The agency has released an annual China Human Capital Report since it initiated the project. In the 2018 report, the Chinese human capital stock in 2015 was estimated as 331.546 trillion $yuan$ at the 1985 price. After adjusting this data using the 2015 price, I have used Eq. (C10) to calculate the Chinese human capital stock in 2016–2030.

$$HC_{t+1} = HC_t \times (1 - deptHC_t) + INVHC_t \tag{C10}$$

In Eq. (C10), HC_{it} is the human capital stock in Year t; $INVHC_{it}$ is the human capital investment in Year t; $deptHC_t$ is the human capital depreciation rate, which is time-invariant. Qian, Wang et al. (2009) comprehensively calculated the depreciation rate (5.14%) of general and professional knowledge and skills in China. I assume that the depreciation rate is the same in the research period as that in Qian, Wang et al. (2009).

According to Jiao and Jiao (2010), human capital can be divided into education, training, health, R&D, and migration. As migration human capital only occupies a small proportion of the whole human capital, I assume that human capital investment consists of the investment on education, training, health, and R&D.

The 2016 China Educational Finance Statistical Yearbook shows that the total national expenditure on education was 3.61 trillion $yuan$ in 2015. As there are no official annual projections of education investment, I have projected the education investment based on National Institute of Education Science (2017) who expected there would be 8.5 trillion $yuan$ of total national expenditure on education in 2030. I assume that the projected education investment will increase linearly in 2015–2030, and the projection is shown in Table C7.

Table C7 The Projected Education Investment in China (Unit: trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Investment	3.61	3.82	4.05	4.29	4.54	4.81	5.09	5.39
Year	2023	2024	2025	2026	2027	2028	2029	2030
Investment	5.70	6.04	6.39	6.77	7.16	7.58	8.03	8.50

According to CreditSuisse (2017), the expenditure on healthcare in China will rise from 611 billion USD in 2015 to 2.3 trillion USD in 2030. I assume that the healthcare investment will increase linearly, and the exchange rate will remain constant at the 2015 level in the studied period. The projected health investment is shown in Table C8.

Table C8 The Projected Health Investment in China (Unit: trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Investment	3.81	4.16	4.54	4.96	5.42	5.92	6.47	7.06
Year	2023	2024	2025	2026	2027	2028	2029	2030
Investment	7.72	8.43	9.21	10.06	10.99	12.01	13.11	14.33

According to 2015 R&D Expenditure Statistical Bulletin, the 2015 R&D expenditure in China was 1.42 trillion $yuan$. The national innovation-driven development strategy programme by the Chinese central government shows the proportion of the R&D expenditure on GDP will be 2.8% in 2030. Based on the GDP projection mentioned above, the R&D Expenditure will be 6.40 trillion $yuan$ in 2030. The projected R&D expenditure is also assumed to change linearly over the research period, and it is shown in Table C9.

Table C9 The Projected R&D Investment in China (Unit: trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
investment	1.42	1.57	1.73	1.92	2.12	2.34	2.59	2.86
Year	2023	2024	2025	2026	2027	2028	2029	2030
investment	3.17	3.50	3.87	4.28	4.73	5.23	5.79	6.40

Unlike education, health, and R&D, to my best knowledge, training investment doesn't have official projections in 2030. According to CIconsulting (2018), the Chinese educational training market was projected to increase by 12% annually to over 3 trillion $yuan$ in 2020. I assume that the training market will continue to grow by 12% annually in 2021–2030. The projected training investment is shown in Table C10.

Table C10 The Projected Training Investment in China (Unit: trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
Investment	1.66	1.96	2.20	2.46	2.75	3.08	3.45	3.87
Year	2023	2024	2025	2026	2027	2028	2029	2030
Investment	4.33	4.85	5.44	6.09	6.82	7.64	8.55	9.58

The depreciation rate of the human capital is difficult to obtain, as the perpetual inventory method is used to calculate the human capital stock. I assume that the annual depreciation rate of human capital is equivalent to the inflation rate. The projected inflation rate in China is from OECD (2014), shown in Fig. C3. Hence, the projected human capital stock is calculated and shown in Table C11 where the data have been adjusted to the 2015 price level. Table C11 shows that the human capital stock in China will grow steadily over the research period.

Table C11 The Projected Human Capital Stock in China (Unit: trillion $yuan$)

Year	2015	2016	2017	2018	2019	2020	2021	2022
stock	1555.81	1571.38	1590.35	1613.89	1642.51	1676.63	1716.68	1763.15
Year	2023	2024	2025	2026	2027	2028	2029	2030
stock	1816.59	1877.60	1946.85	2025.09	2113.12	2211.85	2322.29	2445.52

To overcome the paucity of sectoral physical capital data, I have referred to the convergence of the capital-output ratio, which means that the ratio tends to converge towards a steady-state value across countries in the long-term (McQuinn and Whelan 2007). Hence, I assume that sectoral physical capital stock, investment and depreciation are linked to the ratio of sectoral output to the overall output, shown in Eq. (C11). Owing to the unavailability of the sectoral human capital data, I make assumptions on the number of employees and their education years, which are the two main features of human capital (Wang, Liu et al. 2018). As there are no official data of the employees' education years, I assume that the education years are equally distributed across sectors. Therefore, sectoral human capital stock, investment and depreciation are linked to the proportional of sectoral employed labour to the overall labour, shown in Eq. (C12).

$$\begin{cases} PC_{it} = \frac{SGDP_{it}}{\sum_i SGDP_{it}} \times PC_t \\ INVPC_{it} = \frac{SGDP_{it}}{\sum_i SGDP_{it}} \times INVPC_t \\ DEPREPC_{it} = \frac{SGDP_{it}}{\sum_i SGDP_{it}} \times DEPREPC_t \end{cases} \tag{C11}$$

$$\begin{cases} HC_{it} = \frac{L_{it}}{L_t} \times HC_t \\ INVHC_{it} = \frac{L_{it}}{L_t} \times INVHC_t \\ DEPREHC_{it} = \frac{L_{it}}{L_t} \times DEPREHC_t \end{cases} \tag{C12}$$

In Eq. (C11) and (C12), PC_{it} and HC_{it} refer to the physical and human capital stock of Sector i in Year t respectively. $INVPC_{it}$ and $INVHC_{it}$ refer to the physical and human capital investment of Sector i in Year t respectively. $DEPREPC_{it}$ and $DEPREHC_{it}$ refer to the physical and human capital depreciation of Sector i in Year t respectively.

A conventional input-output table shows that a portion of each intermediate transaction reflects the value of pure physical flows, with the remainder being the value of intangible knowledge flows (Jin 2012). Jin (2012) quantified human capital flows embodied in an intermediate transaction, shown in Eq. (C13). int_{ijt} denotes the intermediate inputs from Sector i to j in Year t; hc_{ijt} is the embodied human capital flows from Sector i to j in Year t; INT_{it} is the total intermediate production of Sector i in Year t.

$$\frac{hc_{ijt}}{int_{ijt}} = \frac{\sum_j hc_{ijt}}{\sum_j int_{ijt}} = \frac{INVHC_{it}}{INT_{it}} \Rightarrow hc_{ijt} = \frac{int_{ijt}}{INT_{it}} \times INVHC_{it} \tag{C13}$$

Traditionally, human capital investment was regarded as a competitor for physical capital investment (Alvarez Albelo 1999). The endogenous replacement of physical capital accumulation by human capital accumulation as a prime engine of economic growth was captured in the transition from the Industrial Revolution to modern growth (Galor and Moav 2004). Daniels and Kakar (2017) showed that physical capital has a CES substitution with human capital in the production function. Accordingly, the composite score of capital investment is formed through a CES function, shown in Eq. (C14).

$$INV_{it} = sinv_i \times (SIPC_{it} \times INVPC_{it}^{\frac{\rho_{in,i}-1}{\rho_{in,i}}} + (1 - SIPC_{it}) \times INVHC_{it}^{\frac{\rho_{in,i}-1}{\rho_{in,i}}})^{\frac{\rho_{in,i}}{\rho_{in,i}-1}} \tag{C14}$$

In Eq. (C14), INV_{it} is the total investment of Sector i in Year t; $sinv_i$ is the scale parameter for the investment in Sector i; $SIPC_{it}$ is the share parameter of physical capital investment in Sector i in Year t; $\rho_{in,i}$ is the elasticity parameter between the physical and human capital investment in Sector i.

Dynamic Change of the SAM

$$\begin{cases} CIF_{ne,t} = \frac{GDP_t^*}{GDP_0^*} \times \frac{L_t}{L_0} \times \frac{PC_{ne,t}+HC_{ne,t}}{PC_{ne,0}+HC_{ne,0}} \\ CIF_{et} = \frac{EC_{et}^*}{EC_{e0}^*} \times \frac{L_t}{L_0} \times \frac{PC_{et}+HC_{et}}{PC_{e0}+HC_{e0}} \\ CIF_t^W = \frac{GDP_t^W}{GDP_0^W} \times \frac{L_t^W}{L_0^W} \times \frac{CS_t^W}{CS_0^W} \end{cases} \tag{C15}$$

$$\begin{cases} \widehat{IMU_{ne,jt}} = IMU_{ne,j0} \times \frac{GDP_t^*}{GDP_0^*} \times \frac{L_t}{L_0} \times \frac{PC_{it}+HC_{it}}{PC_{i0}+HC_{i0}} \\ \widehat{IMU_{ejt}} = IMU_{ej0} \times \frac{EC_{et}^*}{EC_{e0}^*} \times \frac{L_t}{L_0} \times \frac{PC_{it}+HC_{it}}{PC_{i0}+HC_{i0}} \end{cases} \tag{C16}$$

The composite influential factor that considers the influence of projected economic growth or energy consumption, effective labour supply, and capital accumulation is defined in Eq. (C15). The ultimate intermediate use part of the SAM table is defined in Eq. (C16). $CIF_{ne,t}$ and CIF_{et} refer to the composite influential factor for a nonenergy and energy sector respectively. The composite influential factor for either an energy sector or nonenergy sector is denoted by CIF_{it}. CIF_t^W is the composite influential factor for the world. GDP_t^W is the world GDP from GDP Long-term Forecast by OECD. L_t^W is the world labour from the world population aged 15–64 in 2017 WPP. CS_t^W is the world capital stock from the CEPII database by Foure, Benassy-Quere et al. (2013). EC_{et}^* is the projected energy consumption given by EIA (2017). $\widehat{IMU_{ne,jt}}$ and $\widehat{IMU_{ejt}}$ refer to the ultimate input of Commodity j in the Output of Nonenergy Sector ne and Energy Sector e respectively.

The 2015 China Input-Output Table shows Compensation of Employees, Net Taxes on Production, Depreciation of Fixed Capital, and Operating Surplus. The dynamic change of these four indexes is shown in Eq. (17). The sectoral output is defined as the summation of these four indexes, whilst the GDP for the country is defined as the summation of the sectoral output, shown in Eq. (C18).

$$\begin{cases} \widehat{YH_{it}} = YH_{i0} \times \frac{N_t^*}{N_0^*} \times CIF_{it} \\ \widehat{GINDTAX_{it}} = GINDTAX_{i0} \times CIF_{it} \\ \widehat{DEPRE_{it}} = DEPRE_{i0} \times \frac{DEPREPC_{it}}{DEPREPC_{i0}} \\ \widehat{OS_{it}} = OS_{i0} \times CIF_{it} \end{cases} \tag{C17}$$

$$\begin{cases} \widehat{SGDP_{it}} = \widehat{YH_{it}} + \widehat{GINDTAX_{it}} + \widehat{DEPRE_{it}} + \widehat{OS_{it}} \\ \widehat{GDP_t} = \sum_i \widehat{SGDP_{it}} = \sum_{ne} \widehat{SGDP_{ne,t}} + \sum_e \widehat{SGDP_{et}} \end{cases} \tag{C18}$$

In Eq. (C17), $\widehat{YH_{it}}$ is the ultimate employees' compensation or household income from Sector i in Year t; $\widehat{GINDTAX_{it}}$ is the ultimate net production taxes of Sector i in Year t; $\widehat{DEPRE_{it}}$ is the fixed capital depreciation of Sector i in Year t; $\widehat{OS_{it}}$ is the ultimate operating surplus of Sector i in Year t. N_t^*

denotes the projected Chinese population in 2017 WPP. $\widehat{YH_{it}}$ is assumed to change with the population growth and composite influential factor. $GIN\widehat{DTAX}_{it}$ and $\widehat{OS}_{it}$ are assumed to change with the composite influential factor only. In contrast, $D\widehat{EPRE}_{it}$ is only related to the estimated physical capital depreciation according to Long and Herrera (2016). In Eq. (C18), $S\widehat{GDP}_{it}$ denotes the sectoral output; $\widehat{GDP}_t$ is the ultimate GDP in Year t.

According to Guo et al. (2014), the sectoral capital input is determined by the sectoral depreciation divided by the depreciation rate, shown in Eq. (C19). The capital income equals the summation of the fixed capital depreciation and the operating surplus, shown in Eq. (C20).

$$K_{it} = \frac{D\widehat{EPRE}_{it}}{dept_i} \tag{C19}$$

$$\widehat{YK_{it}} = D\widehat{EPRE}_{it} + \widehat{OS}_{it} \tag{C20}$$

In Eq. (C19) and (C20), K_{it} is the capital input of Sector i in Year t; $dept_i$ denotes the depreciation rate which is time-invariant; $\widehat{YK_{it}}$ is the capital income from Sector i in Year t. Hence, the household and rest of the world (RW) capital income is defined in Eq. (C21).

$$\begin{cases} \widehat{YHK}_t = YHK_0 \times \frac{N_t^*}{N_0^*} \times \frac{\widehat{GDP}_t}{GDP_0} \\ \widehat{YWK}_t = YWK_0 \times \frac{\widehat{GDP}_t}{GDP_0} \end{cases} \tag{C21}$$

In Eq. (C21), $\widehat{YHK}_t$ is the household capital income in Year t; $\widehat{YWK}_t$ is the RW capital income in Year t. Eq. (C21) implies that $\widehat{YHK}_t$ is assumed to change proportionally to the population growth and GDP, whilst $\widehat{YWK}_t$ is assumed to change proportionally to GDP growth only. The enterprise capital income $\widehat{YEK}_t$ is used as the balancing item of the capital account in the SAM.

As the sectoral output changes over time, the final use part of the SAM also changes. The household consumption is assumed to change proportionally to the population growth and composite influential factor. In contrast, the enterprise, government and RW consumption (export) are assumed to be related to the composite influential factor only.

$$\begin{cases} \widehat{HD_{it}} = HD_{i0} \times \frac{N_t^*}{N_0^*} \times CIF_{it} \\ \widehat{GD_{it}} = GD_{i0} \times CIF_{it} \\ \widehat{INV_{it}} = INV_{i0} \times CIF_{it} \\ \widehat{QM_{it}} = QM_{i0} \times \frac{N_t^*}{N_0^*} \times CIF_{it} \\ \widehat{QE_{it}} = QE_{i0} \times \frac{N_t^W}{N_0^W} \times CIF_{it}^W \\ GT\widehat{RIFM}_{it} = GTRIFM_{i0} \times CIF_{it} \end{cases} \tag{C22}$$

In Eq. (C22), $\widehat{HD_{it}}$ is the adjusted household consumption of Commodity i in Year t; $\widehat{GD_{it}}$ is the adjusted government consumption of Commodity i in Year t; $\widehat{INV_{it}}$ is the adjusted total capital investment of Sector i in Year t; $\widehat{QM_{it}}$ is the adjusted import of Commodity i in Year t; $\widehat{QE_{it}}$ is the adjusted export of Commodity i in Year t; $GTR\widehat{IFM}_{it}$ is the adjusted import tax of Sector i in Year t; N_t^W is the projected world population from the medium-variant scenario in 2017 WPP. Eq. (C22) implies that $\widehat{HD_{it}}$ and $\widehat{QM_{it}}$ are assumed to change proportionally to the Chinese population and composite influential factor, whilst $\widehat{QE_{it}}$ is assumed to change proportionally to the population and composite influential factor in the world. In contrast, $\widehat{GD_{it}}$, $\widehat{INV_{it}}$, and $GTR\widehat{IFM}_{it}$ are assumed to change proportionally to the composite influential factor only. The sectoral stock change STO_{it} is used to balance the commodity account in the SAM.

$$\begin{cases} \widehat{YHG}_t = YHG_0 \times \frac{N_t - L_t}{N_0 - L_0} \times \frac{\widehat{GDP}_t}{GDP_0} \\ \widehat{YHW}_t = YHW_0 \times \frac{N_t^*}{N_0^*} \times \frac{GDP_t^W}{GDP_0^W} \\ GH\widehat{TAX}_t = GHTAX_0 \times \frac{L_t}{L_0} \times \frac{\widehat{GDP}_t}{GDP_0} \\ \widehat{SH}_t = SH_0 \times \frac{N_t^*}{N_0^*} \times \frac{\widehat{GDP}_t}{GDP_0} \end{cases} \tag{C23}$$

In Eq. (C23), $\widehat{YHG}_t$ is the adjusted governmental income transfer to the household in Year t; $N_t - L_t$ is the non-working-age population in Year t; $\widehat{YHW}_t$ is the adjusted household income from the rest of the world (RW) in Year t; $GH\widehat{TAX}_t$ is the adjusted household income tax paid to the government in Year t; $\widehat{SH}_t$ is the adjusted household saving in Year t. $\widehat{YHG}_t$ will change proportionally to the Chinese non-working-age population and GDP, whilst $\widehat{YHW}_t$ will change proportionally to the Chinese population and world GDP. $GH\widehat{TAX}_t$ will change proportionally to the Chinese working-age population and GDP, whereas $\widehat{SH}_t$ will change proportionally to the Chinese population and GDP. The enterprise money transfer to the household $\widehat{YHE}_t$ is used to balance the household account in the SAM.

$$\begin{cases} GE\widehat{TAX}_t = GETAX_0 \times \frac{\widehat{GDP}_t}{GDP_0} \\ \widehat{YWG}_t = YWG_0 \times \frac{\widehat{GDP}_t}{GDP_0} \\ \widehat{GWY}_t = GWY_0 \times \frac{GDP_t^W}{GDP_0^W} \end{cases} \tag{C24}$$

In Eq. (C24), $GE\widehat{TAX}_t$ is the adjusted direct tax of the enterprise paid to the government in Year t. $\widehat{YWG}_t$ is the adjusted governmental money transfer to the RW in Year t. $\widehat{GWY}_t$ is the adjusted RW money transfer to the government in Year t. $GE\widehat{TAX}_t$ and $\widehat{YWG}_t$ will change proportionally to the Chinese GDP, whilst $\widehat{GWY}_t$ will change proportionally to the world GDP. The enterprise saving $\widehat{SE}_t$ is used to balance the enterprise account in the SAM. The government saving $\widehat{SG}_t$ is used to balance the government account in the SAM. The RW saving $\widehat{SF}_t$ is used to balance the RW account in the SAM.

The welfare change resulting from the carbon tax is measured by the Hicks Compensation Variation (CV) and Equivalent Variation (EV). The CV means that the amount of the additional money an entity needs to reach its initial utility after the price changes, whilst the EV is the income change at the current prices as if the price equivalently changes.

$$CV = \sum_t CV_t = \sum_t \sum_i (PQ_{it} \times HD_{it} - PQ_{it} \times HD_{i0}) \quad \text{(C25)}$$

$$EV = \sum_t EV_t = \sum_t \sum_i (PQ_{i0} \times HD_{it} - PQ_{i0} \times HD_{i0}) \quad \text{(C26)}$$

In Eq. (C25) and (C26), the subscript "0" denotes the reference scenario where no carbon tax is implemented; CV_t and EV_t denote the compensation variation respectively. A positive sign of the CV (EV) implies that the carbon tax will increase the social welfare, whilst a negative sign of the CV(EV) not necessarily means climate policies will incur the loss of social welfare owing to the underestimation of the ancillary benefits (only one pollutant is analysed), letting aside the primary benefits of these policies, including damage, such as rising sea level and wildlife extinction, averted from climate change.

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