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The Boundary of Porter Hypothesis: The Energy and Economic Impact of China's Carbon Neutrality Target in 2060

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Abstract: The process of carbon neutrality does have economic costs; however, few studies have measured the cost and the economic neutral opportunities. This paper uses a dynamic computable general equilibrium (CGE) model to simulate China's carbon neutrality path from 2020 to 2060 and analyzes its economic impact. This paper innovatively adjusts the CGE modeling technology and simulates the boundary of the Porter hypothesis on the premise of economic neutrality. The results show that the carbon neutrality target may reduce the annual GDP growth rate by about 0.8% in 2020–2060. To make the carbon pricing method under the carbon neutrality framework meet the strong version of the Porter hypothesis (or economic neutrality), China must increase its annual total factor productivity by 0.56–0.57% in 2020–2060; this is hard to achieve. In addition, the study finds that China's 2030 carbon target has little impact on the economy, but the achievement of the 2060 carbon neutrality target will have a significant effect. Therefore, the paper believes that the key to carbon neutrality lies in the coexistence of technological innovation and carbon pricing to ensure that we can cope with global warming with the lowest cost and resistance.

Keywords: carbon neutrality; China; economic impact; computable general equilibrium model; carbon tax; carbon emission trading scheme

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1. Introduction

This paper studies the possible economic impact of China's carbon neutrality process and studies how many total factor productivity increases can make up for the economic losses; that is, under what conditions the strong version of the Porter hypothesis can be established. The strong version of the Porter hypothesis [1] means that reasonable and strict environmental regulation can stimulate enterprise innovation and hedge the costs caused by environmental regulation.

1.1. Background and Motivation

Many countries have announced their target goals on carbon neutrality. In the low-carbon development process, EU countries are at the forefront of the world both in technologies and management [2,3]. The EU proposes to achieve the goal of carbon neutrality by 2050, and China has announced the goal of carbon neutrality in 2060, indicating that nearly 1/3 of the world's emissions will go zero in 2060 [4,5]. However, no matter how we talk about carbon neutrality, we still need to consider the economics of carbon neutrality because there is indeed a strong trade-off between emission mitigation and economic development [6–8], regardless of many opposite hypotheses, such as the Porter hypothesis [9,10].

If the cost of emission mitigation is beyond expectation, governments may reduce their interest in reducing emissions.

Certainly, measuring the cost of emission mitigation, especially carbon neutrality, is essential for us human beings. The existing literature has estimated the marginal cost or efficiency cost of emission mitigation in many ways from different perspectives. Qin et al. (2019) [11] simulated the cost-effectiveness of China's green transition during the 12th five-year plan (2011–2015). Wang et al. (2016) [12] found that different regions have totally different abatement costs (measured by shadow price), and potential emissions (measured by the growth rates of emissions and economic outputs), highlighting the importance of specializing the carbon mitigation policies among the different regions. Cui et al. (2014) [13] applied a computable general equilibrium model to simulate the cost-saving effect of the emission trading scheme (ETS) and found that the carbon emissions trading only covered the pilots and that the unified carbon emissions trading market could reduce the total abatement costs by 4.50% and 23.67%.

However, only measuring the economic cost may not be enough. The economic cost varies by space and time. Using the directional distance function model, Wang et al. (2020) [14] measured the policy effects on CO_2 emission mitigation and abatement costs during the 13th Five-Year Plan (2016–2020) in China. They found high emission mitigation targets accompanied by high emission reduction costs. In the short term, the impact on different targets is not that obvious, but as time goes by, the effect increases. Uncertainties also affect the cost. Guo et al. (2019) [15] used a stochastic dynamic programming model to evaluate the impacts of uncertainties on the abatement planning process and found that uncertainties could increase the total abatement costs by around 5–7%.

Reducing the cost of the carbon mitigation policy is an essential topic of emission mitigation strategies [16]. Scholars have focused on the following methods: the clean development mechanism (CDM) [17], certified emission reduction (CER), carbon linkage, and low-carbon technologies. Wang et al. (2016) [18] analyzed the cost–benefit of waste-to-energy projects under China's clean development mechanism. They found that with or without the CDM, there is still a huge GHG reduction potential in solid waste management in China, which may reduce the cost of emission mitigation in China. Li et al. (2019) [19] found that the Chinese Certified Emission Reduction (CCER) scheme saves the national carbon trading system costs by applying a game theory. Zhang et al. (2019) [20] found that carbon linkage could reduce China's ETS pilots' carbon emission trading scheme's cost. Sun et al. (2018) [21] argued that most low-carbon technologies are cost-effective, with average annual cost savings of 71.43 billion CNY. Johansson et al. (2020) [22] found that the biofuels mandate in the United States reduced the emission reduction cost significantly, ranging up to 20 USD per ton. The Canadian case study finds a similar perspective [23].

Similar to the perspectives in the literature above [13], this paper also considers carbon pricing as a relatively cost-effective way to reduce emissions. Carbon pricing has proven effective in many regions and has been studied from many perspectives [24–27]. Among them, carbon emission trading schemes and carbon tax (CT) are two of the most popular mitigation strategies.

In 1990, the Netherlands began to levy a carbon tax: one of the earliest countries in the world to impose carbon taxes [28]. Sweden and Denmark also have strong and effective carbon tax policies [29–31]. The carbon tax policies of many countries, such as the United States, Australia, France, China, and Japan, are full of twists and turns. However, in most of these countries, a new kind of carbon pricing occurred: ETS. California seems to be the only state in the USA that has implemented a cap-and-trade scheme since 2013 [32]. EU-ETS is the first and the largest ETS in the world currently [33,34]. In 2010, the world's first city-level compulsory emission trading system was established in Tokyo, Japan. Then, Saitama Prefecture established the emission trading system in 2011. Saitama Prefecture's ETS is mainly a copy of the Tokyo ETS [35]. China's ETS pilot started in 2013 [36], and China's national ETS has already officially commenced on July 16, 2021. The revenue recycling scheme is one of the most concerning topics that may affect emission mitigation efficiency. For example, Liu and Lu (2015) [37] argued that the recycling scheme matters in the long-term effect of the carbon tax and the sectors' burden. Sun et al. (2021) [38] designed a recycling scheme to improve the emission mitigation effect and reduce the gross domestic product (GDP) loss.

Until now, there have been many studies focusing on the comparison of carbon pricing strategies [39]. However, it seems that there is little in the literature focusing on the economic losses of the strategies and no paper measuring how much of the productivity should be improved to neutralize the economic losses, or in other words, the boundary of the Porter hypothesis. It is the knowledge gap that this paper wants to fill. To fill the gap, the paper first measures the GDP loss of ETS and CT under carbon neutrality, then focuses on the changes by carbon neutrality and the boundary of the strong Porter hypothesis using CGE modeling technology.

1.2. Contributions and Paper Structure

Although existing papers focus on carbon neutrality, little in the literature studies the economic cost of carbon neutrality by applying carbon pricing [40–42]. Thus, this paper wants to fill the knowledge gap, for exploring the impact of carbon neutrality by emission trading and carbon tax from the perspective of GDP loss, energy structure, the compensation of the total factor productivity, and commodity price. The specific contributions and findings of the paper are shown below:

1. The paper finds that the cost of achieving carbon neutrality is in reducing the average annual growth rate in 2020–2060 by about 0.8%. The annual growth rate of the GDP will decrease from 1.2% to 1.8% in 2050–2060.
2. Carbon tax and carbon trading can significantly increase the share of renewable energy and make the energy system cleaner. Coal consumption in the counterfactual scenario will be cut in half compared with the benchmark, and the total energy demand will be reduced significantly because of the high actual energy prices.
3. If the whole society wants to make up for the loss of GDP, then in 2020–2060, society's average annual total factor productivity (TFP) must increase by 0.56–0.57% compared with the benchmark scenario. In other words, an additional 0.56–0.57% of the annual TFP growth could meet the strong Porter hypothesis.
4. The improvement of TFP can further stimulate the renewable energy structure and may reduce the producer's price of all kinds of goods. Therefore, technological progress may be the key to reducing the negative impact of achieving the carbon neutrality target.

The rest of the paper is organized as follows: Section 2 is the scenario design, which is the paper's exogenous assumptions. Section 3 introduces the paper's methodology, including the introduction of the computable general equilibrium (CGE) model used in the article, the dynamic method, and the data source. Section 4 presents the results of carbon neutrality impacts during 2020–2060 and discusses the results. Section 5 further assumes that the increase in TFP makes the process of carbon neutrality economically neutral (no impact on GDP), then presents and discusses the results. Section 6 discusses the key results found in the paper and compares them with other examples in the literature. Section 7 concludes the paper's results and proposes policy implications.

2. Scenario Design

The most important part of carbon neutrality is carbon emissions. This paper does not consider the impact of adding negative carbon emission technology at present because if negative carbon emission technology is to be added (such as forest carbon sequestration and carbon capture), more assumptions will be included in the model, which may affect the robustness of the model's conclusions.

We need to consider the remaining emissions by fossil energy consumption which are challenging to replace, such as air transportation, marine transportation, and energy chemicals, that will be captured by negative carbon emission technology. The paper calculates the emission share of these sectors from the total emissions in 2019 from the CEADs database (https://www.ceads.net.cn/, accessed on 1 November 2022) to be about 9%. Considering how other sectors may have positive emissions (increasing remaining emissions) and land transportation may be substituted by electric vehicles (reducing remaining emissions), the paper holds the assumption of 9% remaining. Thus, we have assumed a significant reduction in carbon emissions by 2060 caused by carbon neutrality measures such as ETS and CT, which is 91% lower than the baseline (BAU) scenario (Figure 1). Although negative carbon emission technology is not included in the model, we still need to assume the existence of negative carbon emission technology to ensure the reliability of the scenario simulation.

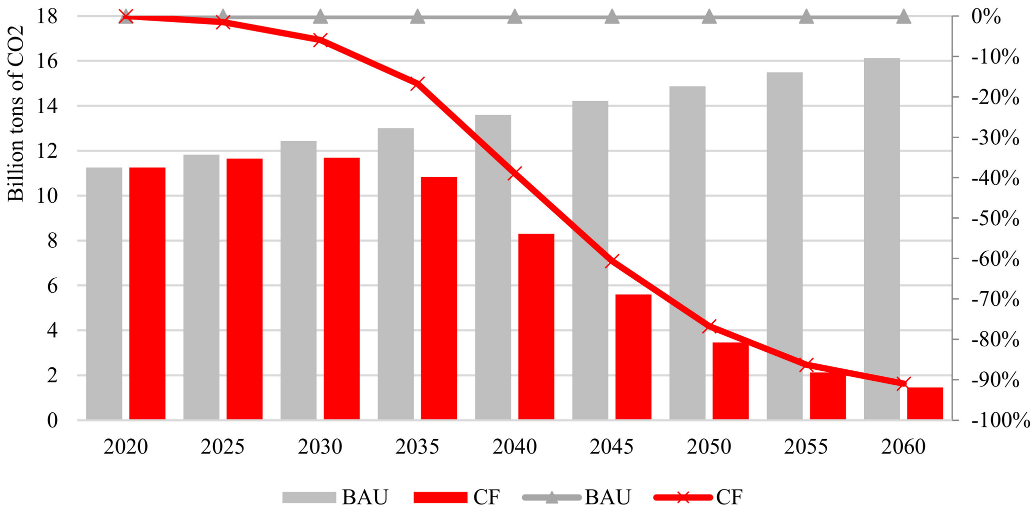


Figure 1. Energy-related CO_2 emissions during 2020-2060 in all scenarios. Notes: the bar chart shows the carbon emissions in 2020-2060 under different scenarios. The line chart shows the reduction rate of carbon emissions in the CF scenarios in each year compared with the BAU scenario. The CF scenarios include the ETS and the CT scenarios, which are illustrated in Table 1.

Table 1. The first scenario design.

Scenario Design	Descriptions
BAU	Assuming that there are no carbon pricing measures.
CT	Assuming that carbon tax is imposed in 2021 and full carbon tax coverage will be introduced in 2040.
ETS	Assuming that carbon emission trading is constructed in 2021 and full coverage of ETS will be introduced in 2040.

This paper assumes that China mainly uses carbon pricing to achieve the goal of carbon neutrality. The carbon tax is a long-discussed carbon pricing strategy for Chinese policymakers. Although a national carbon trading market was online in 2021, the current carbon trading market only covers the power generation industry, mainly because of the poor quality of data detection [43]. Therefore, a carbon tax may be a supplementary policy for China's carbon trading market or may even become the primary emission mitigation strategy.

In other words, at present, the carbon trading mechanism is relatively mainstream, and the positive stimulating effect of such a mechanism on enterprises seems to be more pronounced. Therefore, China may gradually improve the quality of monitoring, reporting, and verification (MRV) and cover more industries in the carbon trading system. Thus, ETS may also become the primary emission mitigation strategy in China.

Therefore, this paper first considers the construction of a CGE model based on the benchmark scenario, named the BAU scenario, and then constructs the CGE model based on the carbon tax or carbon trading scenario under the carbon neutrality framework and then compares the results of the carbon neutrality scenarios and the BAU scenario through similar analyzing methods for the experimental group and the control group. The scenario design is shown in Table 1. The paper assumes that the coverage of CT and ETS is in line with China's government plan; all the energy-intensive industries will be covered by carbon pricing [44]. Moreover, in 2040, carbon pricing will cover all kinds of enterprises.

3. Methodology

3.1. CGE Model

3.1.1. Why Do We Choose CGE Model?

Generally speaking, if we want to simulate an event that does not actually happen, and the event will lead to significant changes in the economic structure, the data-driven empirical evidence model will no longer be applicable, such as the econometric model (for example, the panel model, generalized method of moment model, time-series model), and machine learning (such as the BP neural network algorithm, genetic algorithm, and hybrid algorithm).

Therefore, when considering the simulation of 2060 carbon neutrality, we need to use the scenario analysis model, which is good at simulating counterfactual events. For example, the LEAP (long-range energy alternatives planning system) model, system dynamics, DSGE (dynamic stochastic general equilibrium) model, and the CGE model.

However, among these scenario analysis models, only the CGE model can describe the relationship between industries in detail because the CGE model is the model with the largest data demand (requiring the input-output table and other data, energy, and emission data of various departments), and it is also a model with relatively weak assumptions. The CGE model can simulate the behavior of maximizing the utility/profit of enterprises, residents, governments, and foreign manufacturers. Additionally, the model considers the mutual restriction relationship between different actors.

3.1.2. The Brief Introduction of CGE Model

The model is widely used to simulate various policies' macro impact [45–47]. This paper's CGE model is from the existing literature, and the exogenous parameters in the model are basically passed through several rounds of inspection [48–50], and the substitution elasticity is set based on a well-known CGE model [51,52]. The CGE model constructed in this paper includes more than 3200 endogenous variables and corresponding equations. It considers the behavior patterns of residents, enterprises, the government, and international firms. It is mainly based on a general equilibrium theory (advanced theory of game theory) and a large number of microeconomic theories (such as manufacturer behavior theory, resident consumption theory, etc). In order to couple the energy and environment block, we additionally considered the relevant theories of energy economics and environmental economics.

The applied model's name is the China Energy-Environment-Economy Analysis 2.0 (CEEEA) model, and it is a dynamic recursive model considering multi-sector and multi-households. The flow chart for establishing and simulating the CGE model is shown in Figure 2. It has five blocks:

1. Production block. This block describes the production behavior in all sectors. These behaviors are simulated by the constant elasticity of substitution (CES) production function considering the energy input, labor input, capital input, Leontief technology, and the intermediate inputs aggregation.
2. Trade block. The block expresses the import behavior of domestic consumers and the export behavior of domestic sectors. The former is simulated by the CES function, and the latter is simulated by constant elasticity of transformation (CET) technology.
3. Income and expenditure block. This block expresses the cash flow among four main economic entities: government, households, firms, and the foreign world.
4. Energy and environment block. The block describes the relationship between energy use in the energy balance table and energy input in the input-output table, the rela-

tionship between energy use and CO_2 emissions, and the carbon pricing strategies of the government.

5. Macroscopic closure and market-clearing block. This block is used to simulate the closure conditions and market-clearing assumptions of the whole economy. Based on the neoclassical macro-closure conditions, the model considers the clearing of commodity and factor markets and assumes that there is no factor redundancy or shortage.

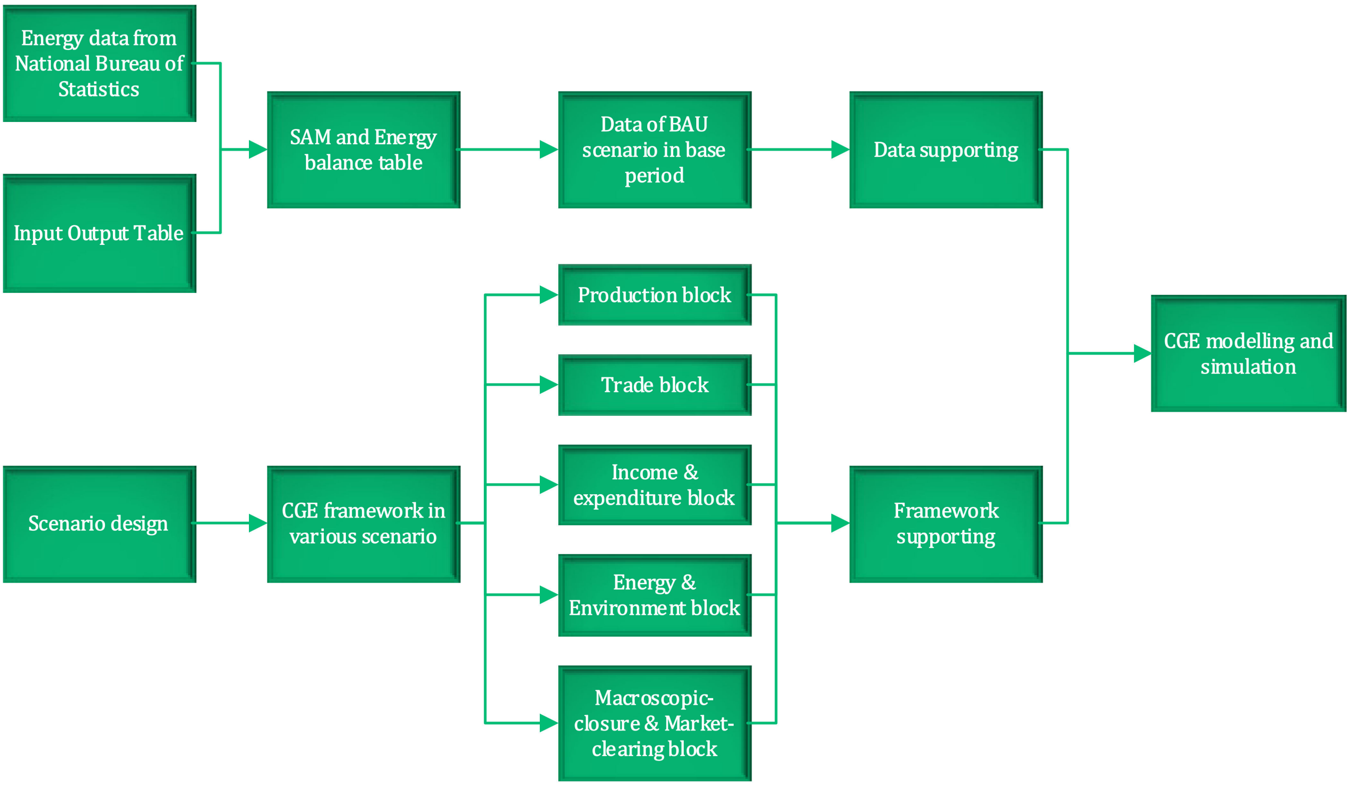


Figure 2. Flow chart of constructing and simulating the CGE model.

3.2. Dynamics

In this paper, the recursive method is used to make the CGE model dynamic. In general, the dynamic strategy under Neoclassical assumptions entails the growth of labor endowment, capital endowment, and technological progress. This paper makes fundamental assumptions about labor growth and calculates capital endowment using the perpetual inventory method. This paper simulates the total factor productivity (TFP) by setting exogenous GDP as an economic growth path and endogenous TFP first. Then, the paper uses TFP as the exogenous variable to simulate all scenarios, considering the steady technological progress.

Except for carbon pricing and leading to different carbon emission pathways, this paper assumes that all exogenous variables in the counterfactual (CF) scenario are the same as in the BAU scenario. The model additionally assumes the same total CO_2 emissions in the CT and ETS scenarios. The significance of this assumption is that it is assumed that the government's carbon pricing parameters are used to control the total amount of carbon emissions, and that the CT and ETS scenarios have the same carbon emissions making the scenario comparison more scientific.

3.3. Data Source

Most of the data in China's input-output table, the energy consumption data in China's energy statistical yearbook, and CO_2 emission data in the CEADs database are required in the model. Based on these data, the study compiles a social accounting matrix and energy balance table. The paper re-classifies the sectors, as presented in Table 2.

Table 2. Sector classification.

Abbreviation of the Sectors	Sectors
AGR	Primary industry
COL	Coal mining
COLP	Coal processing
O_G	Oil and gas exploitation
REFO	Refined oil
REFG	Refined gas
OMIN	Other mining's
LGT	Other mining industries
CMC	Chemicals
BMTL	Building material
STL	Steel
MTL_P	Metal products
MFT	Manufacturing
THP	Thermal power
HYP	Hydropower
WDP	Wind power
NCP	Nuclear power
SOP	Solar power
CST	Construction
TSPT	Transportation
SER	Services

At present, the latest input-output table has been updated to 2020, but we have not adopted it. The main reasons are: (1) The 2020 table is an extended table based on the 2017 table, and there may be a larger difference between the intermediate input value in the table and the actual situation. (2) The year 2020 witnessed the COVID-19 pandemic, so the data on transportation, tourism, and other industries cannot reflect the normal economic operation. Therefore, in order to ensure the reliability of the simulation, we conducted the simulation based on the table in 2018 (there was no input-output table in 2019). In addition, we believe that the epidemic will eventually pass and that society will gradually return to normal. Therefore, it is significantly better to simulate the relationship among industries, households, and government with data in 2018 than with data in 2020.

This paper obtains the physical quantity of energy consumption in various industries through China's energy statistical yearbook. However, the energy consumption data by industry in the China energy statistics yearbook is different from the industrial division in this paper, and the article integrates the sectors. For the sectors that need to be split, this paper separates them through the corresponding input-output coefficient.

Data on carbon emissions. Based on the calculated energy consumption data of re-classified sectors, IPCC's carbon emission calculation references and data, such as the average low calorific value, carbon content per unit calorific value, and carbon oxidation rate, are calculated in this paper through the carbon dioxide emission of these sectors.

Tax and resident income. The cash flow among the government, households, and firms is also simulated in this paper. So, factor income and direct tax are required and derived from the CEIC database (https://www.ceicdata.com/en, accessed on 1 November 2022).

It should be noted that if we have IOT from different regions and some relevant data, after sector adaptation and parameter calibration, the model can be used in any country with data support. However, due to the difference in the industry classification, productivity level, and trade relations in different countries, the results will be very different. Therefore, although the model in this paper can be applied to most countries, the research conclusion can only be considered unchanged.

4. Simulation Results

4.1. The Basic Situation in the BAU Scenario

The BAU scenario is the benchmark scenario of the paper; that is, almost all results are based on the comparison between the CT/ETS scenario and the BAU scenario. So, the paper needs to report the basic information about the BAU scenario first.

The CO_2 emissions in 2060 will be about 16.1 billion tons, increasing by 43% compared with 2020 emissions, which is illustrated in Figure 1. In terms of the primary energy structure, in the BAU scenario in 2060, China's primary fossil energy accounts for 32.0%, and the primary electricity (renewable energy) accounts for 68.0%. The energy structure is much better than the current situation, but there is still a big gap from in carbon neutrality goal.

Because this paper uses a long-term model, we do not consider using Keynesian macro closure conditions but neoclassical macro closure conditions. That is, the factor is fully utilized. Therefore, the main constraints of the whole model come from factor endowment. Thus, in the dynamic process, this paper considers the technological progress and changes in factor endowment (Section 3.2). The changes in capital and labor endowments and technological progress will lead to an increase in GDP. Without carbon constraints, the GDP in the BAU scenario will increase to 739 trillion CNY in 2060, with the primary sectors accounting for 9.3%, the secondary sectors accounting for 25.2%, and the tertiary sectors accounting for 65.5%. In the labor market, the labor population of the primary sectors accounts for 16.9%. Among them, the secondary sectors account for 16.0%, the tertiary sectors account for 65.5%, and the tertiary industry accounts for 67.1%.

4.2. Impacts on GDP

Figure 3 shows the impact of CT and ETs on the gross domestic product (GDP). The bar shows the GDP every five years, and the line shows the average annual growth rate of these five years. In the BAU scenario, China's GDP growth rate gradually decreases. The growth rate will be 5.5% in 2020–2025 but will reduce to 4.50% in 2055–2060. The BAU scenario's GDP settings are similar to several relevant studies. For instance, compared with Fang et al. (2015) [53], the path is pessimistic about the GDP growth from 2020 to 2040 but relatively optimistic from 2040 to 2060. However, in general, it is a fairly optimistic estimate compared with the other literature [54] because this paper considers that China is a developing country with a vast population and is implementing the rural revitalization strategy, so there is still much room for GDP growth in rural and backward areas.

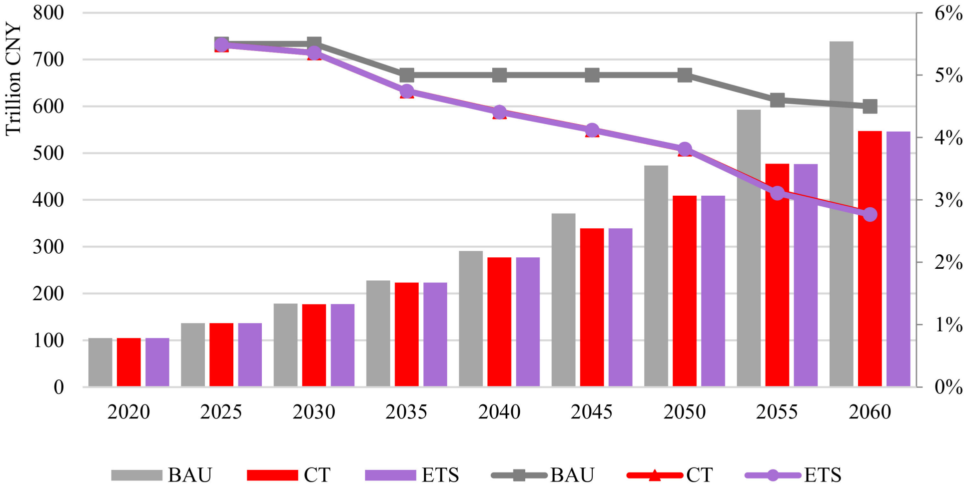


Figure 3. Impacts on GDP during 2020–2060.

Note that from 2021 to 2060, the average annual growth rate of the CT scenario was 4.23%, and in the ETS scenario, the average annual growth rate was 4.22%, indicating that the growth rate in the two counterfactual scenarios is similar to each other. As under the same emission mitigation path, there may be little differences between the economic impact of the full coverage carbon tax and carbon trading [39].

In the long run, it seems that there is no apparent difference in the impact of the carbon tax and carbon trading covering the same industry and emission mitigation on the total economy. In the early stage of the carbon neutrality process (2020–2040), the economic loss caused by the carbon pricing method will not be substantial. However, with the strict carbon emission reduction targets, economic losses gradually increased. From 2035 to 2040, the target of carbon neutrality will reduce economic growth by 0.6%; from 2055 to 2060, the economic growth will decrease by 1.7% in the final period of carbon neutrality. In summary, in the year 2020–2060, the average growth rate of the BAU scenario is about 5.0%, while the average growth rate under the carbon-neutral framework is around 4.2%: a decrease of about 0.8%.

4.3. Impacts on the Energy Mix

As renewable energy is the key to further energy supply [55], we need to focus on the energy mix in the long-term simulation. Figure 4 illustrates the impacts on the primary energy structure in 2060 and the energy mix in the 2020 BAU scenario. The electric power industry is the main source of carbon emissions in China, especially the coal-fired plant [56]. In the BAU scenario, the primary fossil energy has significantly reduced to 32.0% in 2060. A total of 21.0% of the primary energy is from coal consumption, and oil and gas account for 11.04%, while renewables account for 68.0%. Under China's current investment situation (dynamic investment preference of each scenario), China's renewable energy will significantly thrive and accounts for a large share. However, coal still accounts for about 1/5 of the primary power. Many examples in the literature also believe that the carbon pricing mechanism may increase the renewable energy share, consistent with relevant research [57,58].

In CT and ETS scenarios, coal consumption will be nearly cut in half in 2060. Moreover, the share of renewables will increase by 3.7–4.8%. The increase will be more significant in the ETS scenario by 4.8%. The percentage of oil and gas will increase by 6.0% and 4.8% in CT and ETS scenarios, respectively. However, the increasing share does not mean increasing consumption, as the total energy demand will significantly reduce under carbon neutrality scenarios. Under the carbon neutrality target, it seems that oil will be more difficult to remove than coal. The main reason for this may be that oil is more inclined to be used by the transportation industry and service industry, which is somehow irreplaceable, especially in air and water traffic.

4.4. Impacts on the Producer Price Index

Figure 5 depicts the impact on all sectors' producer price indexes in 2060. We found that energy-intensive industries are the most vulnerable sectors when achieving carbon neutrality targets. Energy processing sectors, such as the processing of coal, oil, and gas (COLP, REFO, and REFG), will be the first three most affected sectors. The results are similar to the relevant literature [59,60]. The prices in 2060 will increase by more than 300% compared with the 2060 BAU scenario. Steel and thermal power prices will increase by about 200% because coke (COLP sector) and raw coal (COL sector) are among the main upstream products of steel and thermal power. The rise in raw materials is a significant factor in the price rises of these sectors.

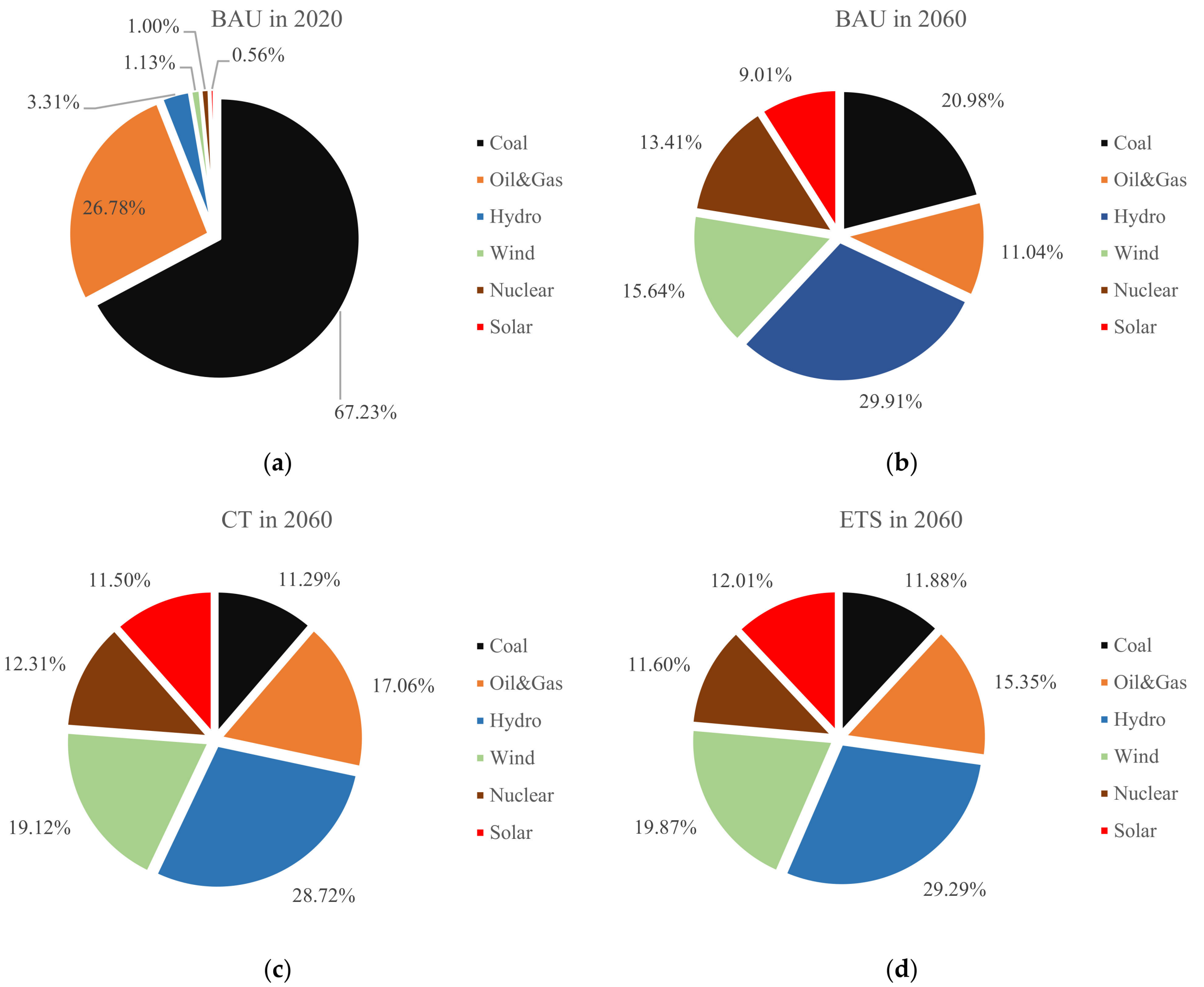


Figure 4. Impacts on energy structure in 2060. (**a**) BAU scenario in 2020; (**b**) BAU scenario in 2060; (**c**) CT scenario in 2060; (**d**) ETS scenario in 2060.

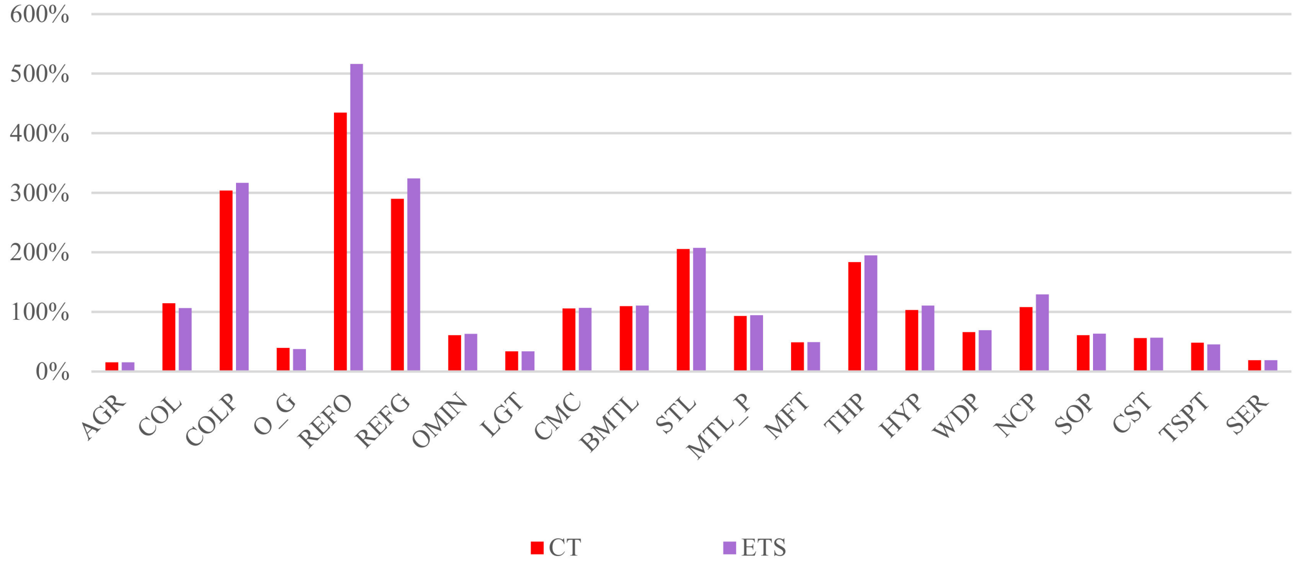


Figure 5. Impacts on producer price index in 2060.

In addition, we noticed that the price of low energy-intensive sectors, such as agriculture and services, may not be affected too much by the carbon neutrality target. The price of agriculture and services will increase by about 17.5% and 18.5%, respectively. The price rises in these industries may be caused by the combined effects of the price rise of other industries.

5. The Boundary of Porter Hypothesis under Carbon Neutrality

5.1. Scenario Design

The Porter hypothesis is an important issue related to carbon constraint. The weak version of the hypothesis describes how appropriate environmental regulations will stimulate technological innovation, while the strong version expresses that environmental regulation positively affects total factor productivity (TFP) or business performance by stimulating technological innovation. This paper focuses on TFP to test the boundary of the Porter hypothesis rather than green productivity, such as in many papers [61] because the definition of the strong version of the hypothesis is productivity.

The two types of carbon pricing models studied in this paper belong to environmental regulation. Therefore, the article wants to simulate the border of the Porter hypothesis in the CT and ETS scenarios. In the CGE model, the TFP of the sector is given exogenously. Therefore, the CGE model implies a critical assumption: the carbon pricing strategy will not affect the change in TFP. Thus, the model cannot use the CGE model to directly verify whether the Porter hypothesis is valid in a region. However, it can study the boundary of the Porter hypothesis through modeling technology: the changes in endogenous and exogenous variables. This section intends to discuss how much additional TFP is needed to increase and meet economic neutrality under carbon neutrality. In other words, what the study wants to know in this section is how much more TFP the enterprise needs to improve and meet the carbon neutrality target without reducing GDP.

Based on this idea, additional research and designs are carried out. We first add the endogenous TFP exchange rates to the scale factor in the CES production function in a value-added bundle and make GDP exogenous to be the same as BAU's GDP. Specifically, the modeling technology changes can be described in the CES production function and GDP calculation, as presented in Equations (1) and (2):

$$\mathrm{Y}_{it} = \mathrm{A}_{it}\left(\sum\nolimits_j \delta_{ij} Input_{ijt}^{\rho_i}\right)^{1/\rho_i} \tag{1}$$

$$\mathrm{GDP}_t = \sum\nolimits_i (XP_{it} + XG_{it} + XV_{it} + EX_{it} - IM_{it}) \tag{2}$$

where Y_{it} is the gross output in sector i and period t. The sector produces goods and services through the CES production function technology. A_{it} is the TFP in sector i and period t. δ_{ij} is the share parameter of input j in the production process by sector i, and ρ_i is the elasticity parameter. $Input_{ijt}$ is the total input of factor j in period t. GDP_t is the gross domestic product in period t, while XP_{it}, XG_{it}, XV_{it}, EX_{it}, and IM_{it} are household consumption, government consumption, investment, export, and import.

Usually, A_{it} is the exogenous variable and GDP_t is the endogenous variable in the model, which means that we performed the comparative analysis based on the same technology level, and we can analyze different external shocks on GDP or other endogenous variables. However, this section wants to explore the border of the strong version of the Porter hypothesis. So, the TFP should be the endogenous variable, and GDP should be controlled to be equal to BAU's GDP in other scenarios. Therefore, the paper changes the model by Equations (3) and (4):

$$\mathrm{Y}_{it}^{cf} = (1+\vartheta)\mathrm{A}_{it}\left(\sum\nolimits_j \delta_{ij} Input_{it\ ijt}^{cf\,\rho_i}\right)^{1/\rho_i} \tag{3}$$

$$\overline{\mathrm{GDP}_t} = \sum\nolimits_i \left(XP_{it}^{cf} + XG_{it}^{cf} + XV_{it}^{cf} + EX_{it}^{cf} - IM_{it}^{cf}\right) \tag{4}$$

where ϑ, which is an endogenous variable that catches the changes in TFP in the condition of the same GDP. The variables with superscript cf denote that they are endogenous variables in this section whose values are different from those in the previous section. $\overline{\mathrm{GDP}_t}$ is an exogenous variable, which is the same in all scenarios in this section. Other settings are the same as in Section 4. The scenario design in this section is described in Table 3.

Table 3. The second scenario design.

Scenario Design	Descriptions
BAU	Assuming that there are no carbon pricing measures.
CT-TFP	Assuming that carbon tax is imposed in 2021 and full coverage of carbon tax will be introduced in 2040. The average TFP will be increased additionally to meet economic neutrality.
ETS-TFP	Assuming that carbon emission trading is constructed in 2021 and full coverage of ETS will be introduced in 2040. The average TFP will be increased additionally to meet economic neutrality.

5.2. Results

5.2.1. Additional TFP: Boundary of Strong Porter Hypothesis

Figure 6 depicts the additional TFP needed for economic neutrality during 2020–2060. The additional TFP required for carbon peak (2030) is not large, but after 2035, a higher TFP growth is needed every year to maintain GDP unchanged. For reaching the emission peak, only an additional 0.056% of total factor productivity per year is required to keep the GDP unchanged during 2020–2030. In contrast, 0.564–0.568% additional TFP is needed per year during 2020–2060 to keep the GDP unchanged for the carbon neutrality goal in 2060. It shows that the difficulty of carbon neutrality may be far more incredible than that of carbon peaking. To achieve the goal of carbon neutrality, we may need both policy guidance and technological change.

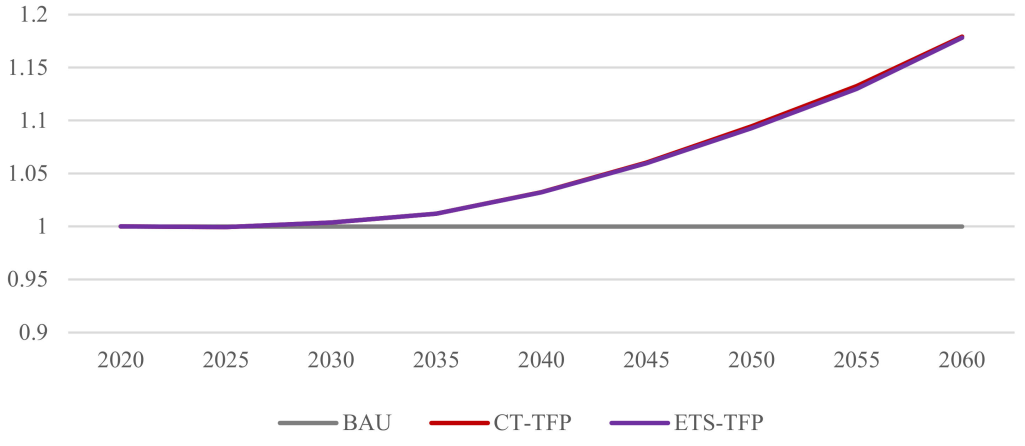
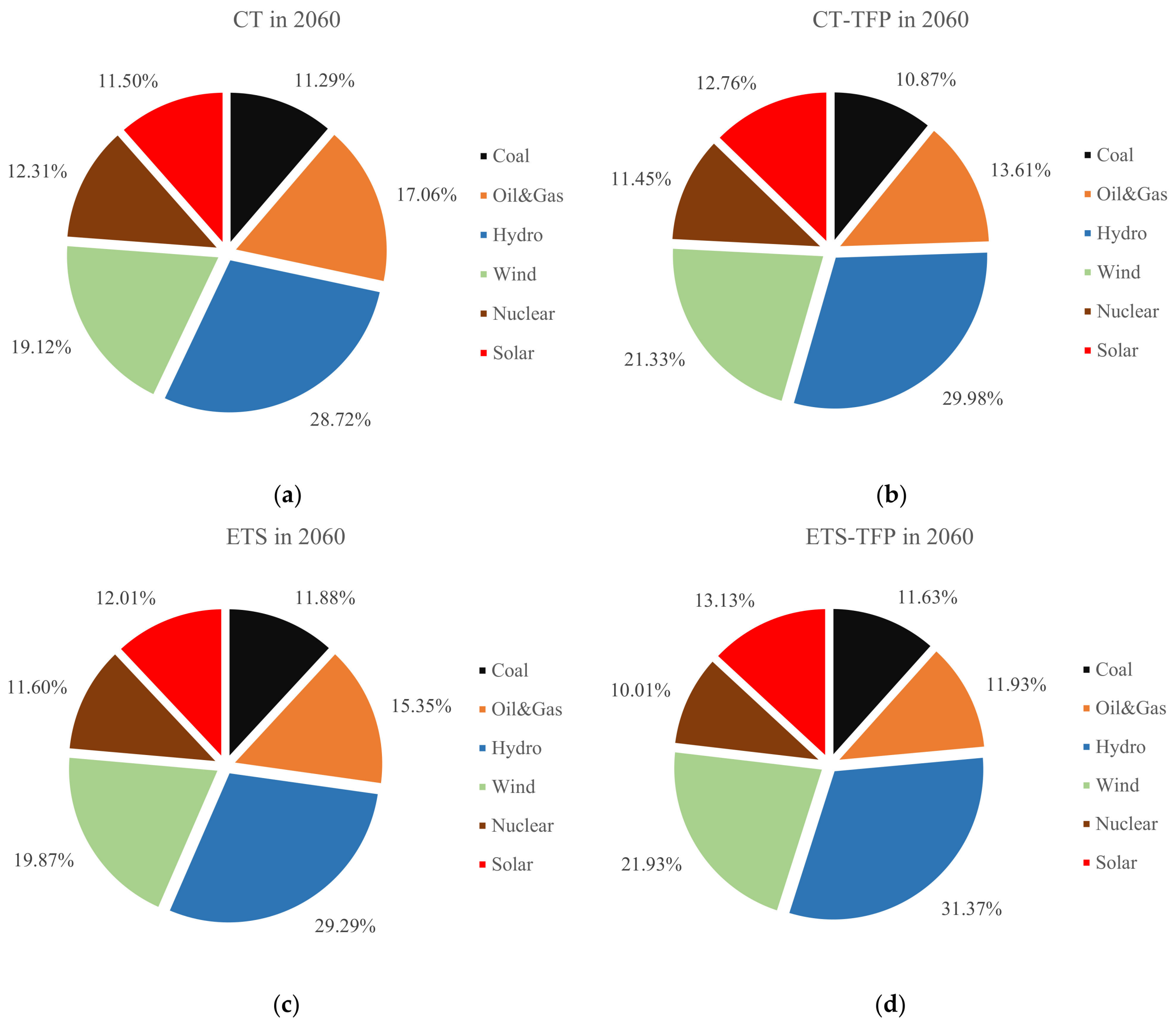


Figure 6. Additional TFP needed for economic neutrality during 2020–2060 (five-year smoothing index).

5.2.2. Impacts on the Energy Mix

Figure 7 illustrates the energy structure of all countermeasure scenarios. To better compare the impact of TFP improvement, we also put the CT scenario and the ETS scenario into Figure 7 for better comparative analysis. The results show that an increase in TFP will further increase the share of renewable energy. The share of renewables will increase by 3.7–3.9% in CT-TFP and ETS-TFP scenarios compared with that in CT and ETS scenarios. A possible reason is that technological progress leads to the increase in TFP, which leads to lower prices and higher demand. Simultaneously, due to the limitation of carbon emissions, more energy demand can only be satisfied by the growth of renewable energy. Thus, TFP growth may increase the share of renewable energy under the constraint of carbon emissions.



(**a**) (**b**) (**c**) (**d**)

Figure 7. Impacts on energy structure in 2060. (**a**) CT scenario in 2060; (**b**) CT-TFP scenario in 2060; (**c**) ETS scenario in 2060; (**d**) ETS-TFP scenario in 2060.

5.2.3. Impacts on PPI

Figure 8 expresses the PPI changes. Due to the improvement of TFP, PPI changes in various products and services show apparent inconsistency. Specifically, the prices of energy-intensive commodities (such as refined oil and refined gas) have increased to a certain extent. Nevertheless, the PPI of non-energy-intensive enterprises, such as agriculture, light industry, and service industry, has decreased significantly.

The overall PPI is declining, but there is heterogeneity in the PPI of different industries. The main reason is that the increase in total factor productivity reduces the production cost of enterprises, so the overall price will decrease. However, due to the constraints of carbon emissions under the carbon neutrality target, carbon pricing will increase due to the increased energy demand, which will increase the product prices of energy-intensive enterprises.

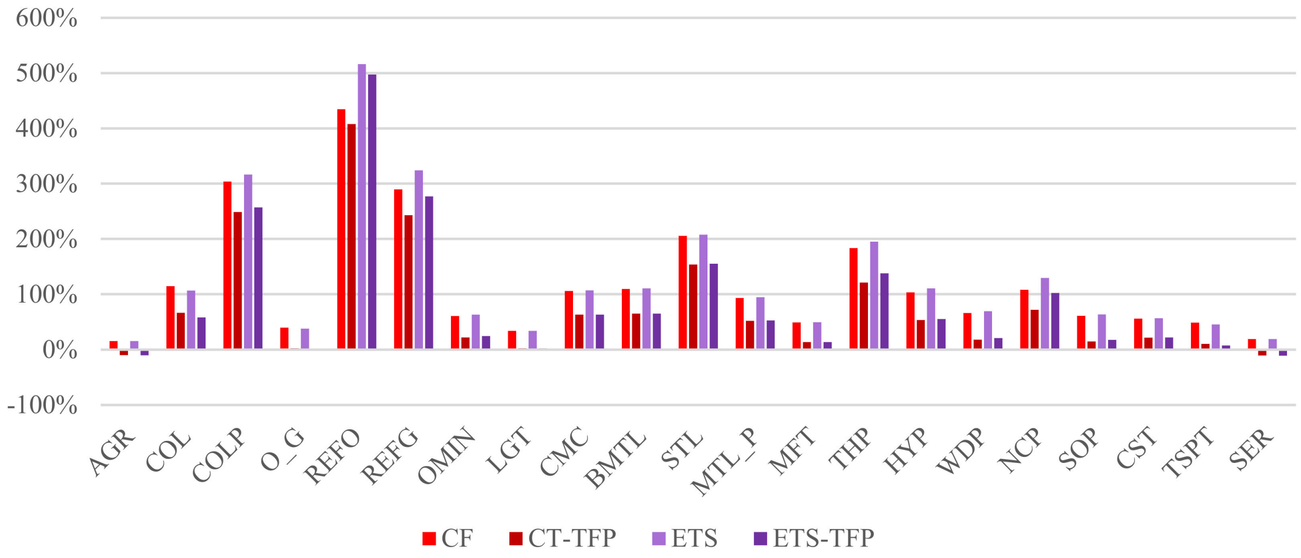


Figure 8. Impacts on producer price index in 2060.

6. Discussions

The results of this paper show that the economic cost of carbon neutralization is very large. If we want to make up for this part of the economic loss, we need an additional TFP growth of about 0.564–0.568% per year.

How difficult is the 0.564–0.568% annual additional TFP growth? According to Park (2012) [62], the TFP growth in most Asian countries (such as China, Japan, Korea, Thailand, Pakistan, and India) will range from 0.95% to 2.66% during 2010–2030. Additionally, the US's TFP growth ranged from 0%–3% during 2000–2020 [63]. Although we could not find the literature about the long-term TFP growth projection, it is certain that China's TFP growth will no longer be higher than China is used to, and the annual growth rate may range from 1% to 2.5%. Thus, the additional 0.568% TFP growth means that the TFP growth should increase by 22.72% to 56.8%.

The paper also finds other examples in the literature identifying Porter's hypothesis from which to take references. Zhao and Sun (2016) [64] argued that flexible control policies meet the weak Porter hypothesis using 2007–2012 enterprise-level data. Lin and Chen (2020) [65] supported the strong Porter hypothesis in the non-ferrous metal industry using province-industry level data in China. Zhou et al. (2021) [66] found that the weak version hypothesis for China's revised environmental protection law does not hold using the listed company's data. Lanoie et al. (2008) [67] found an average of 3% TFP growth in the Quebec manufacturing sector brought by environmental regulation. Their study has data for six years, so the annual additional TFP growth is about 0.5%, which is similar to this study; however, rather than for the manufacturer, this study is for the whole society. Other examples in the literature on testing the hypothesis also prove how hard it can be made in the context of carbon neutrality.

7. Conclusions, Policy Implications, and Limitations

7.1. Conclusions and Policy Implications

The Chinese government announced the goal of achieving carbon neutrality by 2060. This paper analyzes the impact of carbon pricing (carbon tax and carbon trading) on the economy and energy through the CGE model. In addition, according to the strong Porter hypothesis, this paper constructs new scenarios to explore the additional TFP value under the assumption of GDP neutrality and carbon neutrality, which provides a marginal contribution to the current literature.

This paper simulates carbon pricing (carbon tax and carbon trading) to achieve carbon neutrality in 2060. It was found that achieving the carbon neutrality target would reduce

China's annual economic growth by about 0.6% during 2020–2060. Carbon pricing can significantly reduce the share of fossil energy consumption and reduce overall energy consumption but also partially increase the irreplaceable energy share (such as water and air transportation and oil consumption). The process of carbon neutrality will significantly increase the price of energy-intensive products, such as energy-processing products and steel, and such a process will hardly have a significant impact on agriculture and services.

According to the strong Porter hypothesis, environmental regulations may lead to technological innovation, thus improving enterprise productivity. In addition, this paper simulates the additional total factor productivity needed to recover the economic loss caused by the carbon neutrality target. The results show that TFP needs to increase by about 0.056% every year from 2020 to 2030 to make up for the economic losses caused by the 2030 carbon peak. However, if we want to make up for the economic losses caused by carbon neutrality in 2060, TFP needs to be increased by about 0.568% annually in 2020–2060. From this point of view, the impact of carbon neutrality on the economy may be far greater than that of carbon peaking, and the economic cost should be carefully considered. By referring to the other literature, this paper believes that additional 0.568% annual TFP growth is hard to achieve, not to mention the cost of increasing productivity.

The growth of TFP will lead to improved production efficiency, and the prices of most commodities will be reduced by varying degrees, especially the prices of non-energy-intensive commodities. However, the prices of energy-intensive commodities will rise due to the dual effects of TFP and carbon neutrality. The main reason for this is that the increase in TFP will make the factor demand rise, but due to carbon constraints, the supply of energy-intensive products is restrained. Therefore, in the case of rising demand and limited supply, the price of energy-intensive products will rise relatively. Similarly, the growth of TFP will increase the share of renewable energy, mainly because under the carbon constraint, the additional energy demand must be provided by renewable energy rather than fossil energy. At the same time, the paper also finds that the price of renewable generation increases in TFP-related scenarios, which also shows that the demand for renewable energy will increase with the increase in energy demand and the limitation of thermal power generation.

These conclusions have a specific significance for our scientific understanding of carbon neutrality. TFP in 2020–2030 only needs an additional 0.056% to make up for the economic loss caused by the peak of carbon emissions; however, we need an annual TFP increase of 0.568% to make up for the economic loss caused by carbon neutrality, and the GDP growth loss is about 0.6% every year. Therefore, in the process of carbon neutrality, encouraging enterprise innovation and improving efficiency may be the key to reducing economic loss and welfare loss.

7.2. Limitations

The boundary of the Porter hypothesis in this paper assumes that all industries should increase the same level of TFP growth to meet the economic neutrality goals, and it is not the real case. However, we cannot know the actual change value of TFP in different industries under the carbon neutrality target. Therefore, we need to understand this boundary as the average boundary of additional TFP increases in the total society.

Another potential bias of this paper is that the model does not consider the cost of technological progress. Although the proportion of R&D investment in the total social cost is low, it may increase under carbon neutrality. Therefore, technological progress is not free. This paper has no appropriate reference to describe the cost of technological progress. Thus, the paper may underestimate the boundaries of strong Porter's hypothesis to some extent.

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References

1. Porter, M.E. America' Green Strategy. *Sci. Am.* **1991**, *264*, 168. [CrossRef]
2. Borowski, P.F. Management of Energy Enterprises in Zero-Emission Conditions: Bamboo as an Innovative Biomass for the Production of Green Energy by Power Plants. *Energies* **2022**, *15*, 1928. [CrossRef]
3. Borowski, P.F. Zonal and Nodal Models of Energy Market in European Union. *Energies* **2020**, *13*, 4182. [CrossRef]
4. Fernández-Braña, A.; Feijoo, G.; Dias-Ferreira, C. Turning Waste Management into a Carbon Neutral Activity: Practical Demonstration in a Medium-Sized European City. *Sci. Total Environ.* **2020**, *728*, 138843. [CrossRef] [PubMed]
5. Shi, X.; Zheng, Y.; Lei, Y.; Xue, W.; Yan, G.; Liu, X.; Cai, B.; Tong, D.; Wang, J. Air Quality Benefits of Achieving Carbon Neutrality in China. *Sci. Total Environ.* **2021**, *795*, 148784. [CrossRef]
6. Wang, F.; Li, Y.; Zhang, W.; He, P.; Jiang, L.; Cai, B.; Zhang, J.; Zhang, P.; Pan, H.; Jiang, H. China's Trade-Off Between Economic Benefits and Sulfur Dioxide Emissions in Changing Global Trade. *Earth's Future* **2020**, *8*, e2019EF001354. [CrossRef]
7. Fleischhacker, A.; Lettner, G.; Schwabeneder, D.; Auer, H. Portfolio Optimization of Energy Communities to Meet Reductions in Costs and Emissions. *Energy* **2019**, *173*, 1092–1105. [CrossRef]
8. Yang, Z.; Shao, S.; Yang, L. Unintended Consequences of Carbon Regulation on the Performance of SOEs in China: The Role of Technical Efficiency. *Energy Econ.* **2021**, *94*, 105072. [CrossRef]
9. Ranocchia, C.; Lambertini, L. Porter Hypothesis vs Pollution Haven Hypothesis: Can There Be Environmental Policies Getting Two Eggs in One Basket? *Environ. Resour. Econ.* **2021**, *78*, 177–199. [CrossRef]
10. Wang, Y.; Sun, X.; Guo, X. Environmental Regulation and Green Productivity Growth: Empirical Evidence on the Porter Hypothesis from OECD Industrial Sectors. *Energy Policy* **2019**, *132*, 611–619. [CrossRef]
11. Qin, C.; Wang, J.; Ge, C.; Su, J. Simulating the Cost-Effectiveness of China's Green Transition Based on Emission Reduction Targets during the 12th Five-Year Plan Period. *J. Clean. Prod.* **2019**, *208*, 19–34. [CrossRef]
12. Wang, S.; Chu, C.; Chen, G.; Peng, Z.; Li, F. Efficiency and Reduction Cost of Carbon Emissions in China: A Non-Radial Directional Distance Function Method. *J. Clean. Prod.* **2016**, *113*, 624–634. [CrossRef]
13. Cui, L.-B.; Fan, Y.; Zhu, L.; Bi, Q.-H. How Will the Emissions Trading Scheme Save Cost for Achieving China's 2020 Carbon Intensity Reduction Target? *Appl. Energy* **2014**, *136*, 1043–1052. [CrossRef]
14. Wang, Z.; Chen, H.; Huo, R.; Wang, B.; Zhang, B. Marginal Abatement Cost under the Constraint of Carbon Emission Reduction Targets: An Empirical Analysis for Different Regions in China. *J. Clean. Prod.* **2020**, *249*, 119362. [CrossRef]
15. Guo, J.-X.; Tan, X.; Gu, B.; Qu, X. The Impacts of Uncertainties on the Carbon Mitigation Design: Perspective from Abatement Cost and Emission Rate. *J. Clean. Prod.* **2019**, *232*, 213–223. [CrossRef]
16. Lin, B.; Jia, Z. Economic, Energy and Environmental Impact of Coal-to-Electricity Policy in China: A Dynamic Recursive CGE Study. *Sci. Total Environ.* **2020**, *698*, 134241. [CrossRef]
17. Rahman, S.M.; Kirkman, G.A. Costs of Certified Emission Reductions under the Clean Development Mechanism of the Kyoto Protocol. *Energy Econ.* **2015**, *47*, 129–141. [CrossRef]
18. Wang, Y.; Geng, S.; Zhao, P.; Du, H.; He, Y.; Crittenden, J. Cost–Benefit Analysis of GHG Emission Reduction in Waste to Energy Projects of China under Clean Development Mechanism. *Resour. Conserv. Recycl.* **2016**, *109*, 90–95. [CrossRef]
19. Li, L.; Ye, F.; Li, Y.; Chang, C.-T. How Will the Chinese Certified Emission Reduction Scheme Save Cost for the National Carbon Trading System? *J. Environ. Manag.* **2019**, *244*, 99–109. [CrossRef]
20. Zhang, W.; Zhang, N.; Yu, Y. Carbon Mitigation Effects and Potential Cost Savings from Carbon Emissions Trading in China's Regional Industry. *Technol. Forecast. Soc. Change* **2019**, *141*, 1–11. [CrossRef]
21. Sun, D.-Q.; Yi, B.-W.; Xu, J.-H.; Zhao, W.-Z.; Zhang, G.-S.; Lu, Y.-F. Assessment of CO_2 Emission Reduction Potentials in the Chinese Oil and Gas Extraction Industry: From a Technical and Cost-Effective Perspective. *J. Clean. Prod.* **2018**, *201*, 1101–1110. [CrossRef]
22. Johansson, R.; Meyer, S.; Whistance, J.; Thompson, W.; Debnath, D. Greenhouse Gas Emission Reduction and Cost from the United States Biofuels Mandate. *Renew. Sustain. Energy Rev.* **2020**, *119*, 109513. [CrossRef]
23. Wang, H.; Zhang, S.; Bi, X.; Clift, R. Greenhouse Gas Emission Reduction Potential and Cost of Bioenergy in British Columbia, Canada. *Energy Policy* **2020**, *138*, 111285. [CrossRef]
24. Green, J.F. Does Carbon Pricing Reduce Emissions? A Review of Ex-Post Analyses. *Environ. Res. Lett.* **2021**. [CrossRef]
25. Huang, Y.; Dai, X.; Wang, Q.; Zhou, D. A Hybrid Model for Carbon Price Forecasting Using GARCH and Long Short-Term Memory Network. *Appl. Energy* **2021**, *285*, 116485. [CrossRef]

26. Chen, Z.; Su, Y.; Wang, X.; Wu, Y. The Price Discrimination and Environmental Effectiveness in Carbon Emission Trading Schemes: A Theoretical Approach. *J. Clean. Prod.* **2021**, *283*, 125196. [CrossRef]
27. Zhang, W.-W.; Zhao, B.; Ding, D.; Sharp, B.; Gu, Y.; Xu, S.-C.; Xing, J.; Wang, S.-X.; Liou, K.-N.; Rao, L.-L. Co-Benefits of Subnationally Differentiated Carbon Pricing Policies in China: Alleviation of Heavy PM2.5 Pollution and Improvement in Environmental Equity. *Energy Policy* **2021**, *149*, 112060. [CrossRef]
28. Kok, R. Six Years of CO 2 -Based Tax Incentives for New Passenger Cars in The Netherlands: Impacts on Purchasing Behavior Trends and CO 2 Effectiveness. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 137–153. [CrossRef]
29. Andersson, J.J. Carbon Taxes and CO_2 Emissions: Sweden as a Case Study. *Am. Econ. J. Econ. Policy* **2019**, *11*, 1–30. [CrossRef]
30. Tirkaso, W.T.; Gren, I.-M. Road Fuel Demand and Regional Effects of Carbon Taxes in Sweden. *Energy Policy* **2020**, *144*, 111648. [CrossRef]
31. Hájek, M.; Zimmermannová, J.; Helman, K.; Rozenský, L. Analysis of Carbon Tax Efficiency in Energy Industries of Selected EU Countries. *Energy Policy* **2019**, *134*, 110955. [CrossRef]
32. Tapia Granados, J.A.; Spash, C.L. Policies to Reduce CO_2 Emissions: Fallacies and Evidence from the United States and California. *Environ. Sci. Policy* **2019**, *94*, 262–266. [CrossRef]
33. Bruninx, K.; Ovaere, M.; Delarue, E. The Long-Term Impact of the Market Stability Reserve on the EU Emission Trading System. *Energy Econ.* **2020**, *89*, 104746. [CrossRef]
34. Soliman, A.M.; Nasir, M.A. Association between the Energy and Emission Prices: An Analysis of EU Emission Trading System. *Resour. Policy* **2019**, *61*, 369–374. [CrossRef]
35. Nguyen, D.H.; Chapman, A.; Farabi-Asl, H. Nation-Wide Emission Trading Model for Economically Feasible Carbon Reduction in Japan. *Appl. Energy* **2019**, *255*, 113869. [CrossRef]
36. Qi, S.-Z.; Zhou, C.-B.; Li, K.; Tang, S.-Y. Influence of a Pilot Carbon Trading Policy on Enterprises' Low-Carbon Innovation in China. *Clim. Policy* **2021**, *21*, 318–336. [CrossRef]
37. Liu, Y.; Lu, Y. The Economic Impact of Different Carbon Tax Revenue Recycling Schemes in China: A Model-Based Scenario Analysis. *Appl. Energy* **2015**, *141*, 96–105. [CrossRef]
38. Sun, Y.; Mao, X.; Yin, X.; Liu, G.; Zhang, J.; Zhao, Y. Optimizing Carbon Tax Rates and Revenue Recycling Schemes: Model Development, and a Case Study for the Bohai Bay Area, China. *J. Clean. Prod.* **2021**, *296*, 126519. [CrossRef]
39. Jia, Z.; Lin, B. Rethinking the Choice of Carbon Tax and Carbon Trading in China. *Technol. Forecast. Soc. Change* **2020**, *159*, 120187. [CrossRef]
40. Schreyer, F.; Luderer, G.; Rodrigues, R.; Pietzcker, R.C.; Baumstark, L.; Sugiyama, M.; Brecha, R.J.; Ueckerdt, F. Common but Differentiated Leadership: Strategies and Challenges for Carbon Neutrality by 2050 across Industrialized Economies. *Environ. Res. Lett.* **2020**, *15*, 114016. [CrossRef]
41. Griffiths, S.; Sovacool, B.K. Rethinking the Future Low-Carbon City: Carbon Neutrality, Green Design, and Sustainability Tensions in the Making of Masdar City. *Energy Res. Soc. Sci.* **2020**, *62*, 101368. [CrossRef]
42. Salvia, M.; Reckien, D.; Pietrapertosa, F.; Eckersley, P.; Spyridaki, N.-A.; Krook-Riekkola, A.; Olazabal, M.; De Gregorio Hurtado, S.; Simoes, S.G.; Geneletti, D.; et al. Will Climate Mitigation Ambitions Lead to Carbon Neutrality? An Analysis of the Local-Level Plans of 327 Cities in the EU. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110253. [CrossRef]
43. Lin, B.; Jia, Z. What Will China's Carbon Emission Trading Market Affect with Only Electricity Sector Involvement? A CGE Based Study. *Energy Econ.* **2019**, *78*, 301–311. [CrossRef]
44. National Development and Reform Commission (NDRC) Notice on the Key Tasks for Launching the National Carbon Emissions Trading Market. Available online: https://www.ndrc.gov.cn/xxgk/zcfb/tz/201601/t20160122_963576.html (accessed on 1 January 2020).
45. Sun, Y.; Zhi, Y.; Zhao, Y. Indirect Effects of Carbon Taxes on Water Conservation: A Water Footprint Analysis for China. *J. Environ. Manag.* **2021**, *279*, 111747. [CrossRef] [PubMed]
46. Wang, Z.; Nong, D.; Countryman, A.M.; Corbett, J.J.; Warziniack, T. Potential Impacts of Ballast Water Regulations on International Trade, Shipping Patterns, and the Global Economy: An Integrated Transportation and Economic Modeling Assessment. *J. Environ. Manag.* **2020**, *275*, 110892. [CrossRef] [PubMed]
47. Su, Q.; Dai, H.; Lin, Y.; Chen, H.; Karthikeyan, R. Modeling the Carbon-Energy-Water Nexus in a Rapidly Urbanizing Catchment: A General Equilibrium Assessment. *J. Environ. Manag.* **2018**, *225*, 93–103. [CrossRef]
48. Jia, Z. What Kind of Enterprises and Residents Bear More Responsibilities in Carbon Trading? A Step-by-Step Analysis Based on the CGE Model. *Environ. Impact Assess. Rev.* **2023**, *98*, 106950. [CrossRef]
49. Jia, Z.; Lin, B. CEEEA2.0 Model: A Dynamic CGE Model for Energy-Environment-Economy Analysis with Available Data and Code. *Energy Econ.* **2022**, *112*, 106117. [CrossRef]
50. Jia, Z.; Wen, S.; Liu, Y. China's Urban-Rural Inequality Caused by Carbon Neutrality: A Perspective from Carbon Footprint and Decomposed Social Welfare. *Energy Econ.* **2022**, *113*, 106193. [CrossRef]
51. Lou, F. *Theory and Application of Chinese Economy-Energy-Environment-Tax Dynamic Computable General Equilibrium Model*, 5th ed.; China Social Sciences Press: Beijing, China, 2015; (In Chinese). ISBN 978-7-5161-6423-5.
52. Fujimori, S.; Masui, T.; Matsuoka, Y. *AIM/CGE [Basic] Manual*; Center for Social and Environmental Systems Research, NIES: Frankfurt am Main, Germany, 2012.

53. Fang, X.; Roe, T.L.; Smith, R.B.W. Water Shortages, Intersectoral Water Allocation and Economic Growth: The Case of China. *China Agric. Econ. Rev.* **2015**, *7*, 2–26. [CrossRef]
54. Cao, J.; Dai, H.; Li, S.; Guo, C.; Ho, M.; Cai, W.; He, J.; Huang, H.; Li, J.; Liu, Y.; et al. The General Equilibrium Impacts of Carbon Tax Policy in China: A Multi-Model Comparison. *Energy Econ.* **2021**, *99*, 105284. [CrossRef]
55. Chen, Y.; Shao, S.; Fan, M.; Tian, Z.; Yang, L. One Man's Loss Is Another's Gain: Does Clean Energy Development Reduce CO_2 Emissions in China? Evidence Based on the Spatial Durbin Model. *Energy Econ.* **2022**, *107*, 105852. [CrossRef]
56. Yao, X.; Lei, H.; Yang, L.; Shao, S.; Ahmed, D.; Ismaail, M.G.A. Low-Carbon Transformation of the Regional Electric Power Supply Structure in China: A Scenario Analysis Based on a Bottom-up Model with Resource Endowment Constraints. *Resour. Conserv. Recycl.* **2021**, *167*, 105315. [CrossRef]
57. Azam, A.; Rafiq, M.; Shafique, M.; Yuan, J. An Empirical Analysis of the Non-Linear Effects of Natural Gas, Nuclear Energy, Renewable Energy and ICT-Trade in Leading CO_2 Emitter Countries: Policy towards CO_2 Mitigation and Economic Sustainability. *J. Environ. Manag.* **2021**, *286*, 112232. [CrossRef] [PubMed]
58. Khan, S.A.R.; Yu, Z.; Belhadi, A.; Mardani, A. Investigating the Effects of Renewable Energy on International Trade and Environmental Quality. *J. Environ. Manag.* **2020**, *272*, 111089. [CrossRef]
59. Huang, Z.; Du, X. Toward Green Development? Impact of the Carbon Emissions Trading System on Local Governments' Land Supply in Energy-Intensive Industries in China. *Sci. Total Environ.* **2020**, *738*, 139769. [CrossRef]
60. Zhu, L.; Zhang, X.B.; Li, Y.; Wang, X.; Guo, J. Can an Emission Trading Scheme Promote the Withdrawal of Outdated Capacity in Energy-Intensive Sectors? A Case Study on China's Iron and Steel Industry. *Energy Econ.* **2017**, *63*, 332–347. [CrossRef]
61. Zhang, D. Green Credit Regulation, Induced R&D and Green Productivity: Revisiting the Porter Hypothesis. *Int. Rev. Financ. Anal.* **2021**, *75*, 101723. [CrossRef]
62. Park, J. Total Factor Productivity Growth for 12 Asian Economies: The Past and the Future. *Jpn. World Econ.* **2012**, *24*, 114–127. [CrossRef]
63. Crouzet, N.; Eberly, J. Intangibles, Markups, and the Measurement of Productivity Growth. *J. Monet. Econ.* **2021**, *124*, S92–S109. [CrossRef]
64. Zhao, X.; Sun, B. The Influence of Chinese Environmental Regulation on Corporation Innovation and Competitiveness. *J. Clean. Prod.* **2016**, *112*, 1528–1536. [CrossRef]
65. Lin, B.; Chen, X. Environmental Regulation and Energy-Environmental Performance—Empirical Evidence from China's Non-Ferrous Metals Industry. *J. Environ. Manag.* **2020**, *269*, 110722. [CrossRef] [PubMed]
66. Zhou, D.; Qiu, Y.; Wang, M. Does Environmental Regulation Promote Enterprise Profitability? Evidence from the Implementation of China's Newly Revised Environmental Protection Law. *Econ. Model.* **2021**, *102*, 105585. [CrossRef]
67. Lanoie, P.; Patry, M.; Lajeunesse, R. Environmental Regulation and Productivity: Testing the Porter Hypothesis. *J. Product. Anal.* **2008**, *30*, 121–128. [CrossRef]