How Does China’s Economic Policy Uncertainty Affect the Sustainability of Its Net Grain Imports?

Yuee Li 1 and Jingdong Li 2,3,*

1 School of Economics and Management, Shandong Agricultural University, Tai’an 271018, China; liyuee82@163.com
2 Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
3 Key Laboratory of Regional Sustainable Development Modeling, Chinese Academy of Sciences, Beijing 100101, China
* Correspondence: lijingdong@igsnrr.ac.cn

Abstract: China is a considerable grain importer in the world. However, the sustainability of China’s grain imports has been greatly challenged by its increasing economic policy uncertainty (EPU). This paper constructs the indicators of economic and environmental sustainability of China’s net grain imports and analyzes the impact of its EPU index on these indicators with a Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model to explore how China’s EPU affects the sustainability of its net grain imports. The main conclusions are as follows. (1) The sustainability of China’s net grain imports fluctuated from 2001 to 2019. (2) China’s EPU has a negative impact on the economic sustainability of its net grain imports. A higher EPU index leads to a lower net import potential ratio and higher trade cost. (3) China’s EPU has a significant negative impact on the environmental sustainability of its net grain imports. It has the greatest negative impact on virtual water imports and smaller impact on virtual land imports and embodied carbon emission. Therefore, China’s EPU affects the sustainability of its net grain imports negatively through its impact on its net grain import potential ratio, trade cost, and virtual land, virtual water, and embodied carbon emissions in net grain imports.

Keywords: economic policy uncertainty (EPU); grain imports; sustainability; TVP-SV-VAR model

1. Introduction

China is a major grain importer in the world. Grain imports have increased remarkably since its WTO accession, from USD 3.42 billion in 2001 to USD 40.48 billion in 2019. China’s grain imports have highly concentrated markets, with Brazil, the United States, Argentina, Canada, Ukraine, Uruguay, Australia, France, Thailand, Russia, Vietnam, and Pakistan as leading markets, accounting for 98.33% of its total grain imports in 2019 (as shown in Figure 1). Brazil and the United States are the two greatest markets and account for 57.01% and 17.20% of its total grain imports, respectively, in 2019. China’s grain imports are also highly concentrated in products. Soybean is by far the biggest product for import, accounting for 82.24% of its total grain imports in 2001 and 86.99% in 2019 (UN-Comtrade 2020). With a population of more than 1.4 billion and the transformation of people’s consumption structure, China’s demand for grain will continue to grow, and grain imports will increase accordingly [1].
The sustainability of China’s net grain imports has a significant impact on its own food security, agricultural resources, and environment [2]. China’s food security is greatly challenged, as its demand for grain expanded continuously with a growing population, rapid urbanization, and changing consumption patterns [3]. Therefore, the Chinese government has stipulated that the self-sufficiency rate of staple grain products (rice and wheat) should be maintained above 95% to ensure food security. Grain is highly water consumptive[4], and China’s grain production is highly dependent on irrigation. The scarcity of water resources in China has brought great challenges to agricultural irrigation [5]. In addition, the spatial distribution of arable land and water resources in China does not match, with 65% of cultivated land located in northern China, which accounts for only 18% of its total water resources [6]. Therefore, China’s grain production brings great pressure on land and water resources [7]. International grain trade minimizes consumption of agricultural resources and influences the environment of every country, by encouraging the most efficient production. Therefore, grain imports have become not only an important means for ensuring food security in China but also an important means for alleviating a shortage of resources and reducing pressure on the environment while pursuing sustainable development.

Global grain trade, however, is increasingly influenced by economic policy uncertainty (EPU). For example, the outbreak of COVID-19, which led to obstruction of agricultural production and logistics interruption, has also led to restrictions on grain exports in many countries. Many ASEAN (Asia and Southeast Asia Nations) members have adopted policies for stabilizing price, limiting exports of grain products, and increasing financial support for agriculture to ensure effective supply and market stability of agricultural products. As a result, the approach of ensuring China’s food security and achieving sustainable development through grain imports has been greatly challenged. Therefore, the current study aimed to examine the impact of China’s EPU on the economic and environmental sustainability of China’s net grain imports. It first evaluates the economic sustainability of China’s net grain imports through trade potential ratio and trade cost, as well as through environmental sustainability through the flow of virtual water, virtual land, and embodied carbon emission in grain trade, and then adopts a Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model to study the impact of its EPU on these two aspects of sustainability. It is expected that the findings can provide thoughtful advice that decision-makers can use to regulate and manage China’s net grain imports and to achieve food security and sustainable development. The current study contributes to the existing literature in two ways. First, it examines the sustainability of
China’s net grain imports, from both an economic perspective, including import potential ratio and trade cost, and from an environmental perspective, including the flow of virtual water, virtual land, and embodied carbon emissions. Secondly, it focuses on the impact of China’s EPU on different indicators of the sustainability of its net grain imports.

2. Literature Review

The research on sustainable trade can be traced back to Grossman and Krueger’s research (1991) on the environmental impact of the North American Free Trade Agreement (NAFTA) [8]. According to International Chamber of Commerce (ICC 2018), Global trade: Securing Future Growth, “sustainable trade” is defined as “the business behavior or activity of trading commodities, goods and services that benefits all parties and minimizes the negative impact on society and environment while promoting global sustainable development”[9]. Similarly, the beginning of the WTO agreement put forward the idea of sustainable development of foreign trade—that is, to make reasonable use of world resources in accordance with the goals of sustainable development, seek the protection and maintenance of the environment, and strengthen the measures taken for this purpose in a way consistent with their respective needs and concerns at different levels of economic development. Therefore, sustainable development of foreign trade must consider both economic development and environmental protection.

From the economic perspective, sustainability of trade is reflected in the realization of trade potential and the reduction of trade cost. Trade potential is the maximum trade flow that can be achieved through free trade without trade barriers [10]. Egger [11] took the fitted value of bilateral trade estimated by the traditional gravity model as “trade potential”, which was widely accepted and adopted [12,13]. The trade potential ratio is the ratio of actual trade value to the fitted value[11].Trade cost is the total transaction and transportation cost related to the cross-border goods exchange, which, in a broad sense, includes transportation costs (freight and time costs), policy barriers (tariff and non-tariff barriers), information costs, contract implementation costs, return costs, laws and regulations costs, and local distribution costs [14,15]. As a form of transaction, international trade involves high transaction costs, which hinders international trade and economic integration [16]. Therefore, sustainable development of trade depends on the increase of the trade potential ratio and the decrease of trade cost.

From the environmental perspective, international grain trade entails the transfer of virtual resources. Globally, Tuninetti et al.[17] pointed out that from 2050 to 2080, the world agricultural products trade network will change significantly, and nevertheless, compared with national self-sufficiency, international trade can save 40–60 m3 of water per person per year. China, however, had a surplus in the virtual water trade of agricultural products from 2001 to 2013 [18]. For example, in agricultural trade with Trans-Pacific Partnership Agreement (TPPA) countries, China’s virtual water trade surplus has been expanding [19]. China’s net export of virtual water in agricultural products trade with Italy further aggravates the pressure on water resources [20]. In terms of virtual land resources, the total amount of virtual land trade in global agricultural products trade has been increasing, from 128 million ha in 1986 to 350 million ha in 2016 [21]. China’s agricultural trade contributed an average of 3.27 million ha per year to global land conservation from 1986 to 2009 [22]. It is predicted that agricultural trade will continue to save water and land resources in China and the world [23]. China’s grain imports, soybeans in particular, have been the leading contributor to China’s virtual water and land imports. In addition, grain production also involves carbon footprint, which is the net embodied carbon emission of grain production [24], so grain trade also involves the transfer of carbon emissions. China and the United States are the largest importers of land resources and carbon emissions [25], and Brazil exported about 223.46 million tons
of carbon emissions from soybean exports in 2010–2015, half of which were imported by China [26].

Economic policy uncertainty (EPU) is the risk of economic policy change that cannot be accurately predicted by market participants and that leads to economic fluctuations and changes in the macroeconomic environment [27]. Since the formulation of the EPU index by Baker et al. [28], this index has been borrowed in a number of empirical applications [29,30]. The theoretical and empirical literature shows that high economic uncertainty can harm economic activity [31,32]. With the advancement of globalization and increasing interdependence of economies, international trade is strongly influenced by EPU, especially trade policy uncertainty. Trade policy uncertainty adds to the fixed cost of trade, so exporters are more cautious and often delay their entry into the market [33,34], while the decrease of trade policy uncertainty can remarkably reduce export cost, improve efficiency, and promote enterprise innovation [35]. Trade policy uncertainty is only a very small part of EPU [28]. Exporters are faced not only with trade policy uncertainty but also with the more general economic policy uncertainty in the world. Greenland et al. [36] found that a high EPU of an EFU target market will reduce export to that country significantly.

Researchers have also studied how EPU events influence grain production and trade [37]. For example, the outbreak of COVID-19 led to the decline of agricultural production [38,39], instability of grain market, and price fluctuation [40]. Yao et al. [41] pointed out that if the pandemic hindered China’s soybean imports, China would need to increase the cultivation area by 6.9 times to meet the demand, which would reduce its grain self-sufficiency rate to 63.4%, seriously affecting its food security. Moreover, EPU also has an important impact on the natural resources and environment in every country. For example, He et al. [1] pointed out that the Sino-US trade conflict led to a surplus of soybeans and an increase of grain transportation mileage in the United States, which caused a significant increase in global environmental costs in the short term.

Studies on China’s grain trade show that changes in China’s grain demand structure and production conditions have transformed China’s position in international grain trade from a net exporter to a net importer. Increase of income and advancement of urbanization in China have brought great changes in food demand and consumption structure [42], while scarce agricultural resources and deterioration of the ecological environment constrain agricultural production [43]. To ensure food security and protect agricultural resources and the environment, China must rely on the international market for supply. Since China’s domestic market and international food markets are closely linked, China’s food security will inevitably be greatly influenced by the international trade environment. Therefore, China’s food security must be considered from a global perspective [44].

Despite the research interest in China’s grain trade, few have studied the sustainability of China’s net grain imports from both an economic and environmental perspective. In addition, EPU has considerable impact on trade sustainability, yet it is less studied. This paper studies how EPU affects the sustainability of China’s net grain imports, and the following hypotheses were proposed.

**Hypothesis 1(H1):** EPU has a negative impact on the economic sustainability of China’s net grain imports.

**Hypothesis 2(H2):** EPU has a negative impact on the environmental sustainability of China’s net grain imports.

### 3. Data and Methods

To study the sustainability of China’s net grain imports, based on previous research, this study selected China’s grain import potential ratio [11] and trade cost [16] as indicators of economic sustainability, and selected virtual land imports [23], virtual water imports [17], and embodied carbon emissions [26] as indicators of its environmental sustainability. The mechanism of the impact of EPU on China’s net grain imports was ex-
explored through the analysis of the dynamic impact of the EPU index on these indicators(Figure 2).

Different techniques were adopted to achieve the objectives. The gravity model was used to measure import potential ratio[12,13], an indicator of economics sustainability. The Novy[45] model was adopted to measure the trade cost of China’s grain imports, the other indicator of economic sustainability. Virtual land content, virtual water content, and embodied carbon emissions were adopted to measure virtual land imports, virtual water imports, and embodied carbon emissions in China’s net grain imports, indicators of the environmental sustainability of China’s net grain imports.

3.1. Economic Sustainability

3.1.1. Measurement of Import Potential Ratio

Import potential ratio is the ratio of actual import value to potential value. The trade gravity model proposed by Tinbergen [46] was adapted to measure potential value. This paper selected the imports of wheat, rice, corn, soybean, and other major grain varieties as the explained variable. Explanatory variables first included: the per capita GDP, population and geographical distance, indicators of economic development, domestic demand, and transportation cost, respectively. Moreover, the exchange rate reflects the purchasing power of currency and influences bilateral trade [47]; thus, the exchange rate was included as an explanatory variable. FTA was also included considering that it helps to reduce the trade barrier and promotes trade [13]. The number of TBT/SPS notification to WTO on behalf of China reflects the non-tariff barriers in grain trade [48], so it was also included as an explanatory variable. The hypothesis behind this variable is that the higher the notification number, the lower the trade. The following trade gravity model was then established:

\[
\ln INX_{ij} = \alpha_0 + \alpha_1 \ln AGDP_i + \alpha_2 \ln AGDP_j + \alpha_3 \ln POP_i + \alpha_4 \ln POP_j + \alpha_5 \ln DIS_{ij} + \alpha_6 \ln ER_{ij} + \alpha_7 \ln FTA_{ij} + \epsilon_{ij}
\]

where \( INX_{ij} \) is China’s net grain imports from country \( j \), \( AGDP_i \) is the per capita nominal GDP of China, \( AGDP_j \) is the per capita nominal GDP of grain export country \( j \), \( POP_i \) is the population of China, \( POP_j \) is the population of country \( j \), \( DIS_{ij} \) is the geographical distance between China and country \( j \), \( ER_{ij} \) is the
exchange rate of country $j$’s currency to RMB, $FTA_{ij}$ represents whether China has signed a free trade agreement with export country $j$, and $TBT_{ij}$ represents TBT and SPS notification on grain products submitted to the WTO on behalf of China.

The formula for calculating the import potential ratio is as follows:

$$IPR_{ijt} = \frac{INX_{ijt}}{\hat{INX}_{ijt}}$$  \hspace{1cm} (2)

Where $IPR_{ijt}$ is the import potential ratio at time $t$, $INX_{ijt}$ is the actual value of China’s net grain imports, and $\hat{INX}_{ijt}$ is the fitted value of China’s net grain imports. A smaller import potential ratio means that the actual trade value is much smaller compared with the fitted value.

3.1.2. Measurement of Trade Cost

The Novy model [45] is a micro-founded measure of bilateral trade costs that indirectly infers trade frictions, and it was used to calculate China’s grain trade cost:

$$TCO_{ijt} = \left(\frac{cx_{ijt}cx_{ji}}{cx_{ij}cx_{ji}}\sigma^{(t-1)}\right) - 1$$  \hspace{1cm} (3)

where $TCO_{ijt}$ is the tariff equivalent, which represents the grain trade cost between China and partners, $cx_{ijt}$, $cx_{ji}$ is the domestic grain trade volume of China and partners respectively, $cx_{ij}$, $cx_{ji}$ represents their exports to each other, and $\sigma$ represents the substitution elasticity. Given the trade flow between the two countries, the higher the substitution elasticity, the lower the trade cost between the two countries. This paper referred to Novy[45] for the value of substitution elasticity. It can be inferred from the equation that an increase of bilateral trade as opposed to domestic trade means a decrease of trade costs between the two countries. It should also be noted that this trade cost measure is a relative value of bilateral trade costs to domestic trade costs, rather than an absolute value of bilateral trade costs.

3.2. Environmental Sustainability

3.2.1. Measurement of Virtual Land

The formula for calculating the virtual land content of grain is as follows:

$$VIL_{w,i} = \frac{PS_{w,i}}{BO_{w,i}}$$  \hspace{1cm} (4)

$$TVIL_{w,i} = TR_{w,i} \cdot VIL_{w,i}$$  \hspace{1cm} (5)

where $VIL_{w,i}$ is the virtual land content per unit mass of crop $i$ in province $w$ at time $t(\text{hm}^2/\text{t})$, $PS_{w,i}$ is the planting area of crop $i$ in province $w(\text{hm}^2)$, $BO_{w,i}$ is yield of the crop $j$ in province $w$ ($t$), $TVIL_{w,i}$ is the virtual land imports of the crop $i$ at time $t$, and $TR_{w,i}$ is the import volume of crop $i$.

3.2.2. Measurement of Virtual Water

1. Water Evaporation of Grain ($ET^c$)

With the help of CROPWAT 8.0 provided by FAO, water evaporation of grain ($ET^c_w$) was calculated with reference crop transpiration determined by meteorological parameters ($ET^0_w$) and crop coefficient ($K^c_w$):

$$ET^c_w = K^c_w \times ET^0_w$$  \hspace{1cm} (6)
2. Green Water Footprint of Grain Production ($WF_{green}$)

The green water footprint was calculated by CROPWAT 8.0. The green water evaporation for every 10 day period equals the minimum value between the effective precipitation ($P^e$) and crop evaporation ($ET^i$). Effective precipitation was calculated by the method provided by the USDA SCS in CROPWAT 8.0, and the effective precipitation is different in different cities.

\[
ET^i_{green} = \min(ET^i, P^e)
\]

\[
WF_{green}^i = 10 \cdot ET^i_{green} / Y^i
\]

where $WF_{green}^i$ is the green water footprint of crop $i$ ($m^3/t$), $ET^i_{green}$ is the green water evaporation capacity, $Y^i$ is the unit yield of crop $i$ ($t/hm^2$), $P^e$ is the effective precipitation in the growing period of grain (mm).

3. Blue Water Footprint of Grain Production ($WF_{blue}$)

Blue water footprint of grain production refers to the consumption of blue water during the growing period of grain. Blue water mainly comes from rivers, lakes, and underground aquifers.

\[
EF_{blue}^i = \max(0, ET^i - P^e)
\]

\[
WF_{blue}^i = 10 \cdot ET^i_{blue} / Y^i
\]

where $ET^i_{blue}$ is the evaporation of blue water.

4. Total Water Footprint of Grain Production ($WF_{total}$)

Water footprint of grain production refers to the total amount of water resources consumed in the process of crop growth per unit mass, including green water footprint and blue water footprint, also known as grain water footprint.

\[
WF_{total}^i = WF_{green}^i + WF_{blue}^i
\]

\[
IWF_{it} = WF_{total}^i \cdot INX_{it}
\]

where $IWF$ represents virtual water imports due to net grain imports, and $INX$ is net grain imports.

3.2.3. Measurement of Carbon Emissions

Grain land embodied carbon emissions refers to carbon emitted from the application of fertilizer, pesticide, and agricultural film as well as from irrigation and agricultural machinery. The formula for calculating the embodied carbon emissions per unit of crops is as follows:

\[
CAB^i = \sum A^i_k \cdot E^k
\]

where $CAB^i$ is the embodied carbon emissions per unit of agricultural land of grain $i$ and $A^i_k$ is the $k$ main carbon source factors of unit grain species $i$, including the amount of chemical fertilizer, pesticide, agricultural film and diesel oil, the total planting area, and effective irrigation area, and $E^k$ is the embodied carbon emissions coefficient of various carbon sources. Based on the calculation method proposed in West et al.[49] and Dubey et al. [50], the corresponding emissions coefficients of six carbon sources were obtained, as is shown in Table 1.

\[
INCA_{it} = CAB_{it} \cdot INX_{it}
\]
where \( INCA_i \) represents reduction in total carbon emissions due to net grain imports, and \( INX_i \) is net grain imports.

**Table 1.** Indirect emissions coefficients of grain production.

| Embodied Carbon Emissions Source | Emissions Coefficient | Reference Source |
|----------------------------------|-----------------------|------------------|
| Fertilizer                       | 0.8956Kg/Kg           | American Oak Ridge National Laboratory |
| Pesticide                        | 4.9341Kg/Kg           | American Oak Ridge National Laboratory |
| Agricultural film                | 5.1800Kg/Kg           | Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University |
| Agricultural diesel              | 0.5927Kg/Kg           | IPCC (2006)       |
| Agricultural irrigation          | 25.000Kg/hm²          | Dubey (2009)      |
| Agriculture planting             | 3.1260Kg/hm²          | College of Biology and Technology, China Agricultural University |

3.3. TVP-SV-VAR Model

The TVP-SV-VAR model can be derived from the general Structural VAR model, which can be expressed as:

\[
Ay_t = F_1y_{t-1} + \cdots + F_ky_{t-k} + \mu_t, \quad t = s + 1, \ldots, n
\]  

(15)

where \( y_t \) is a \((k \times 1)\) vector of observed variables; \( A,F_1, \ldots, F_k \) is a \((k \times k)\) matrix of time-varying coefficients; \( \mu_t \) is a \((k \times 1)\) vector of structural impact; assuming that \( \mu_t \sim N(0, \Sigma) \); \( \Sigma \) is a \((k \times k)\) diagonal matrix, and \( A \) is a lower-triangular matrix with the diagonal elements equal to 1.

\[
\Sigma = \begin{bmatrix}
\sigma_1 & 0 & \cdots & 0 \\
0 & \ddots & \cdots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
0 & \cdots & 0 & \sigma_k
\end{bmatrix}, \quad A = \begin{bmatrix}
1 & 0 & \cdots & 0 \\
0 & 1 & \cdots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
0 & \cdots & 0 & 1
\end{bmatrix}
\]  

(16)

Assuming that \( B_i = A^{-1}F_i, i = 1, \ldots, s \), the structural VAR model can be written as:

\[
y_t = B_1y_{t-1} + \cdots + B_sy_{t-s} + A^{-1}\Sigma e_t, \quad e_t \sim N(0, I_s)
\]  

(17)

Define \( \beta \) as the stacked row vector of \( B_i (i = 1, \ldots, s) \); define \( X_t = I_s \otimes (y_{t-1}, \ldots, y_{t-s}) \), where \( \otimes \) stands for the Kronecker product; thus, the reduced-form structural VAR can be expressed as:

\[
y_t = X_t\beta + A^{-1}\Sigma e_t
\]  

(18)

Furthermore, assuming that all parameters are dynamically changing, the model is extended to the form of time-varying parameters:

\[
y_t = X_t\beta_t + A_t^{-1}\Sigma_t e_t, \quad t = s + 1, \ldots, n
\]  

(19)

where \( \beta_t, A_t^{-1}, \Sigma_t \) are time-varying; thus, the above expression is the Time-Varying Parameter VAR model.

According to Nakajima[51], the elements of \( A_t \) are compiled in a vector \( \alpha_t = (a_{21}, a_{31}, \ldots, a_{k+1}) \); define \( h_t = (h_{t1}, \ldots, h_{tk}) \) and \( h_t = \log \alpha_t^0, i = 1, \ldots, k; \quad t = s + 1, \ldots, n \). Thus, assume that the parameters in the TVP-SV-VAR model are following the random walk process:
\[ \beta_{s+1} = \beta_t + \mu_{\beta_t}, \quad \alpha_{s+1} = \alpha_t + \mu_{\alpha_t}, \quad h_{s+1} = h_t + \mu_{ht} \]

\[ \beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0}), \quad \alpha_{s+1} \sim N(\mu_{\alpha_0}, \Sigma_{\alpha_0}), \quad h_{s+1} \sim N(\mu_{ht_0}, \Sigma_{ht_0}) \]

\[ \begin{pmatrix} \epsilon_t \\ \mu_{\beta_t} \\ \mu_{\alpha_t} \\ \mu_{ht_t} \end{pmatrix} \sim N \left( \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_{\alpha} & 0 \\ 0 & 0 & 0 & \Sigma_{ht} \end{pmatrix} \right) \]

Therefore, the impact disturbance between the available time-varying parameters is irrelevant. The MCMC method was used to estimate the parameters of the TVP-SV-VAR model. The steps included: (1) Set \( y = \{y_t\}_{t=1}^n \), \( \omega = (\Sigma_{\beta}, \Sigma_{\alpha}, \Sigma_{ht}) \), \( \pi(\omega) \) is the prior probability density of \( \omega \), set the initial value of \( \beta, \alpha, h \), and \( \omega \); (2) Set the values of \( \alpha, h, \Sigma_{\beta}, \) and \( y \), sample \( \beta \); (3) Set the values of \( \beta, h, \Sigma_{\alpha}, \) and \( y \), sample \( \alpha \); (4) Set the values of \( \beta, h, \Sigma_{ht} \), and \( y \), sample \( \beta \); (5) Set the values of \( \beta, h, \Sigma_{ht} \), and \( y \), sample \( h \); (6) Set the values of \( h, \Sigma_{ht} \), and \( y \), sample \( \beta \); (7) Return to the step(2).

### 3.4 Data Description

The grain products in this study included wheat (HS 1001); barley (HS1003); oats (HS 1004); maize (HS 1005); rice (HS 1006); grain sorghum (HS 1007); buckwheat, millet, and canary seeds (HS 1008); and soya beans (HS 1201). The sample interval in this study was 2001–2019. Because China’s grain trade features imports, accounting for 97.10% of total grain trade in 2019, this study focused on net grain imports, the difference between exports and imports. China’s grain imports data were from the UN-Comtrade database. Data on the per capita nominal GDP of China and grain export countries, population, and the exchange rate of export countries’ currencies to RMB were from the World Bank. Data on the geographical distance between China and export countries came from Distance Calculator. Data about FTA came from the Ministry of Commerce of China. TBT and SPS notification on grain products submitted to WTO on behalf of China were from WTO/TBT-SPS Notification and Enquiry of China. Data on grain production were from FAO, and a country’s domestic trade volume was considered as equivalent to the difference between a country’s total grain production and exports, following the method of Wei [52]. Data of planting area, yield per unit area, and total production of grain crops in China were from the National Bureau of Statistics of China. Data on China’s rainfall came from the China Meteorological Administration. Data on chemical fertilizer, pesticide, plastic film, diesel oil consumption, and irrigation area of China’s grain crops were from the Compilation of Cost-Benefit Data of Agricultural Products in China. The annual CPI fixed base index based on 2001 was used to deflate the various types of data expressed by prices, in order to eliminate the impact of inflation.

The EPU index was from FRED Economic Data and was revised according to the research of Huang et al. [53]. Major events of EPU included China’s WTO accession, the outbreak of SARS, the financial crisis, China’s abolishment of agricultural taxes, 2010 Shanghai World EXPO, change in RMB fixing mechanism, Sino–US trade conflict, and the outbreak of COVID-19 (Figure 3). China’s EPU index fluctuated frequently but showed a significant upward trend from 129.16 in 2001 to 357.69 in 2019. The EPU index was relatively lower in the first period from 2001 to 2007 and became much higher in the second period from 2008 to 2019. In the first period, after its WTO accession in December 2001, China implemented a series of tariff reduction measures to promote trade, and its overall economic and trade environment was improved, so the EPU index decreased. The outbreak of SARS in 2003 had a great negative impact on China’s economy in the short
term, leading to a rising EPU index. In the second period, the world financial crisis and food crisis in 2008 led to a significant rise in the EPU index. A downgrade of the US sovereign credit system in 2011 led to turbulence in the world financial system and a rise of China’s EPU index. The Sino–US trade war in 2018 involved a large amount of trade and a wide range of industries, which greatly hindered the development of these two countries, and China’s EPU index rose remarkably. The outbreak of COVID-19 in 2019 and its global spread in 2020 had a great negative impact on global development and cooperation, and thus led to a sharp increase in China’s EPU index.

![Figure 3. China Economic Policy Uncertainty Index from 2001 to 2019.](image)

**4. Results and Analysis**

4.1. *Sustainability of China’s Net Grain Imports*

4.1.1. Economic Sustainability of China’s Net Grain Imports

1. Net Grain Import Potential Ratio

Panel data of 12 partner countries from 2001 to 2019 were used to estimate the fitted value of China’s net grain imports, and it was important to select the specific form of the grain import model to improve the validity of the empirical results. The F test and Hausman test were used for this purpose. In China’s net grain import model, the P value of the Hausman random effect test was 0.0000, so the individual fixed effect variable intercept model was adopted. This paper estimated the fitted value of net grain imports based on national panel data. The factors influencing net import included per capita nominal GDP, population, geographical distance, exchange rate, FTA, TBT notification, etc., which varied from country to country. Therefore, the choice of the individual fixed effect variable intercept model could examine the regional differences of China’s net grain imports more accurately. After the form of the model was determined, regression analysis of the variables in China’s grain import equation were conducted, and the estimated results of each parameter are shown in Table 2.

It can be seen from the estimation results that the coefficient of China’s per capita nominal GDP is significant at the level of 1% and has the greatest positive impact on China’s net grain imports. China’s population, the population of grain export countries, and China’s TBT notification were significant at the level of 5%. China’s population had a positive impact on its net grain imports, while the population of export countries had a negative impact. China’s TBT had a small negative impact. The coefficient of per capita nominal GDP and exchange rate of export countries were significant at the level of 10%. The negative impact of per capita nominal GDP of export countries was the largest, while the exchange rate had a small positive impact. The coefficient of geographical distance between China and export countries was not significant, indicating that geographical distance was not the main factor affecting China’s net grain imports, as a result of the continuous development of shipping technology. FTA had a positive impact on China’s
net grain imports though not significant, showing that signing of the FTA was beneficial to China’s net grain imports. The reason for its insignificance may be that China had not signed an FTA with major grain export countries (such as the United States, Brazil, Argentina, etc.).

Table 2. Regression results of China’s grain import model.

| Variable | Coefficient | Z-Statistic |
|----------|-------------|-------------|
| LnAGDP_a | 4.630*** | 4.99 | 12.072* |
| LnAGDP_b | -5.849* | -1.59 | -1.91 |
| LnPOP_a | 2.565** | 2.087 | 1.51 |
| LnPOP_b | -2.699*** | -2.25 | 1.78 |
| LnDIS_a | 1.927 | 1.10 | 0.099 |
| LnER_a | 0.224* | -2.192 | 0.049** |
| FTA_t | 0.099 | 1.51 | 0.099 |
| TBT_a | 1.927 | -2.192 | 0.049** |

Note: *、**、***represent significance levels of 10%, 5%, and 1% respectively.

China’s net grain import potential ratio can be evaluated based on net import potential from 2001 to 2019, which can be calculated with estimated values of the parameters in China’s grain import model. The changes of China’s net grain imports, fitted value of net imports, and net grain import ratio are shown in Figure 4. China’s net grain imports grew rapidly from 2001 to 2017 but declined in 2018 and 2019. The fitted value of grain imports also grew from USD 3.43 billion in 2001 to USD 106.12 billion in 2017 but declined to USD 58.09 billion in 2018 and USD 55.34 billion in 2019. China’s grain import potential ratio showed an overall trend of decline from 2001 to 2019 despite the fluctuations. In the first period, from 2001 to 2008, net import potential ratio was at a much higher level, despite frequent fluctuations. Since China’s accession into the WTO, China’s grain import and import potential increased steadily, and the import potential ratio fluctuated frequently. In the second period, from 2009 to 2019, the net import potential ratio decreased more steadily with a slight increase only in 2015. After that, China’s grain import potential ratio decreased very rapidly in 2018 and 2019, when the Sino–US trade war greatly impacted China’s net grain imports, especially soybean imports. Based on Equation (2), it should be noted that smaller potential ratio means that the actual import value was much smaller compared with the fitted value. Therefore, overall decline of net import potential ratio indicates a widening gap between China’s actual grain import and the fitted value.

Figure 4. China’s net grain import potential ratio from 2001 to 2019.

2. Grain Trade Cost

Generally speaking, China’s grain trade cost was decreasing from 2001 to 2017, with fluctuations, but increased greatly in 2018 and 2019 (Figure 5). After China’s WTO accession in December 2001, China had sharply reduced tariffs on grain imports, and grain trade cost dropped from 1.385 in 2001 to 0.920 in 2003. After slight fluctuations, it then
increased greatly to 1.137 in 2008, when major grain export countries restricted grain exports by reducing export quotas or increasing export tariffs during the world food crisis and financial crisis. After 2009, strengthened trade cooperation between China and major grain export countries and the increase of trade in bulk commodities helped to reduce China’s grain trade cost steadily. It then decreased greatly, especially from 2015 to 2017, and reached the lowest value of 0.614 in 2017. However, China’s grain trade cost surged in 2018 after the Sino-US trade conflict broke out and China imposed an additional 25% tariff on US soybeans, and trade cost continued to rise in 2019.

![Figure 5](Figure 5). Trend of grain trade cost from 2001 to 2019.

4.1.2. Environmental Sustainability of China’s Net Grain Imports

The environmental sustainability of China’s net grain imports was evaluated through three indicators: virtual land, virtual water, and embodied carbon emissions in China’s net grain imports. Figure 6 shows the change of these three indicators from 2001 to 2019. Generally speaking, the three indicators experienced a similar trend of development, with gradual increase from 2001 to 2014, dramatic increase in 2015, slight decrease in 2016, remarkable increase in 2017, and very sharp drop in 2018 and 2019. Virtual land and water imports and embodied carbon emissions were the smallest in 2002, which were 6.9832 million hectares, 33.226 billion m³, and 0.164 million tons, respectively. From 2003 to 2014, China’s imports of soybean, barley, rice, and corn increased, as did virtual land, virtual water, and embodied carbon emissions imports. In 2015, the substantial increase of China’s net grain imports led to a significant increase in virtual land and water imports and embodied carbon emissions imports, reaching the value of 102.48 million hectares, 510.58 billion m³, and 3.879 million tons, respectively. The decrease of China’s net grain imports in 2016 led to the decrease of the three indicators. In 2017, the sharp increase of soybean and barley imports led to the largest amount of virtual land imports, virtual water imports, and embodied carbon emissions, which were 113.1179 million hectares, 575.318 billion m³, and 4.2798 million tons, respectively. Virtual land and water imports and embodied carbon emissions plunged in 2018 when China’s soybean imports decreased significantly, as soybean imports have been the main contributor to China’s virtual land and water imports.
4.2. Impact of China’s EPU on the Sustainability of Its Net Grain Imports

4.2.1. TVP-SV-VAR Model Test

This study adopted a TVP-SV-VAR model to analyze the impact of EPU on the sustainability of China’s grain trade because a VAR model is often used to deal with the dynamic relationship between time series and has strong explanatory power for the relationship between variables in an unstable system. Firstly, dimensionless quantization was used to eliminate the influence of variable units on the model results before impulse response. Secondly, stability tests of EPU index, import potential ratio (IPR), trade cost (TCO), virtual land imports volume (TVIL), virtual water imports volume (IWF), and embodied carbon emissions volume (INCA) were conducted, and a further cointegration test was needed for the non-stationary series. Finally, impulse response analysis of TVP-SV-VAR model was carried out for the stationary sequence and non-stationary sequence with cointegration. The ADF test results of each series are shown in Table 3. The series of EPU index, IPR, and TVIL did not pass the stability test, and the first-order difference series all passed the stability test. Therefore, the cointegration test was carried out for these non-stationary series.

Table 3. Unit root test.

| Variable | Test type (C,T,L) | ADF-Statistic | 1% Critical-Value | 5% Critical-Value | p-Value | Result |
|----------|------------------|---------------|-------------------|-------------------|---------|--------|
| EPU      | (C,T,1)          | -2.4264       | -4.6162           | -3.7104           | 0.3547  | non-stable |
| ΔEPU     | (0,0,0)          | -4.1046       | -2.7080           | -1.9628           | 0.0004  | stable |
| IPR      | (0,0,0)          | -1.4098       | -2.6997           | -1.9614           | 0.1424  | non-stable |
| ΔIPR     | (0,0,0)          | -4.0542       | -2.7080           | -1.9628           | 0.0004  | stable |
| TCO      | (0,0,0)          | -2.6213       | -2.6997           | -1.9614           | 0.0120  | stable |
| TVIL     | (0,0,0)          | -0.9493       | -2.6997           | -1.9614           | 0.2925  | non-stable |
| ΔTVIL    | (0,0,0)          | -4.6456       | -2.7080           | -1.9628           | 0.0001  | stable |
| IWF      | (C,T,0)          | -4.0333       | -4.6678           | -3.7332           | 0.0300  | stable |
| INCA     | (C,T,0)          | -3.9037       | -4.6678           | -3.7332           | 0.0375  | stable |

Note: In the test type, C, T, and L denote the intercept, trend, and lag periods in ADF test, respectively.

The cointegration test results of EPU index, import potential value, and virtual land imports volume series are shown in Table 4. It can be seen that there is cointegration among the non-stationary sequences, so they were used for TVP-SV-VAR model analysis.
Table 4. Cointegration test.

| Numbers | Characteristic-Value | Trace-Statistics | 5% Critical-Value | p-Value |
|---------|----------------------|-----------------|------------------|--------|
| None†  | 0.831520             | 57.82437        | 35.01090         | 0.0000 |
| At most 1* | 0.749623           | 27.54844        | 18.39771         | 0.0020 |
| At most 2* | 0.209988            | 4.007032        | 3.841466         | 0.0453 |

Based on Nakajima [51], the following equation is stipulated: \( \sum \beta = \mu \alpha = \mu_h = 0 \), \( \sum \rho = \sum \alpha = \sum \beta = 1 \). Furthermore, prior assumption is made that \( \sum \rho \), \( \sum \alpha \), \( \sum \beta \) are diagonal matrices and satisfy the following requirements: \( \sum \rho \sim \text{Gamma} (40.002) \), \( \sum \alpha \sim \text{Gamma} (4.02) \), \( \sum \beta \sim \text{Gamma} (4.02) \). The parameters of the TVP-SV-VAR model were estimated by using the MCMC method to simulate 10,000 samples. The results are shown in Table 5.

Table 5. The estimation results of MCMC simulation.

| Parameter | Posterior-m | P-Standard Error | 95%L | 95%U | Con. D-Value | Influence-F |
|-----------|-------------|------------------|------|------|--------------|-------------|
| \( \Sigma_{\beta_1} \) | 0.0023 | 0.0003 | 0.0018 | 0.0029 | 0.182 | 2.03 |
| \( \Sigma_{\beta_2} \) | 0.0023 | 0.0003 | 0.0018 | 0.0029 | 0.447 | 1.35 |
| \( \Sigma_{\alpha_1} \) | 0.0055 | 0.0016 | 0.0034 | 0.0096 | 0.140 | 6.92 |
| \( \Sigma_{\alpha_2} \) | 0.0055 | 0.0016 | 0.0033 | 0.0094 | 0.492 | 3.65 |
| \( \Sigma_{h_1} \) | 0.0029 | 0.0004 | 0.0022 | 0.0039 | 0.992 | 1.17 |
| \( \Sigma_{h_2} \) | 0.0029 | 0.0004 | 0.0022 | 0.0039 | 0.540 | 1.13 |

Note: \( \Sigma_{\beta_1}, \Sigma_{\beta_2}, \Sigma_{\alpha_1}, \Sigma_{\alpha_2}, \Sigma_{h_1}, \Sigma_{h_2} \) represent the estimation results of the first two diagonal elements of the posterior distribution, respectively, and the results of the remaining elements on the diagonal are similar; 95% L is the lower limit of the 95% confidence interval, and 95% U is the upper limit of the 95% confidence interval.

Table 5 shows the posterior mean value, posterior standard deviation, the bounds of 95% confidence interval, Geweke convergence diagnostic value, and invalid influence factor of each parameter in the two models. It can be seen that the posterior mean values of all parameters in the model are within the 95% confidence interval, and the diagnostic values of Geweke convergence are less than the critical value of 1.96 of 5%. Therefore, the null hypothesis of convergence to posterior distribution was not rejected. In this model, the maximum invalid influence factor of the parameters was 6.92, which indicates that the MCMC sampling results satisfied the posterior inference of the TVP-SV-VAR model, with at least 1445 valid samples obtained in 10,000 samples. The first row of Figure 7 represents the autocorrelation coefficient of the sample, the second line represents the sample path, and the third line represents its posterior density. It can be seen that the autocorrelation coefficient of the sample decreases rapidly, and the sample path is basically stable, which indicates that the subsequent inference of the model is reliable.
4.2.2. Impulse Response Results

1. Impact of China’s EPU on the Economic Sustainability of Its Net Grain Imports
   (1) Impact of China’s EPU on Its Grain Import Potential Ratio

   As seen in the impulse response results of the impact of EPU on China’s grain import potential ratio, the standard deviation impact of EPU random interference term had a significant negative impact on China’s grain import potential ratio, and the negative impact was time-varying, as shown in Figure 8a.

   Firstly, EPU had a negative impact on China’s grain import potential ratio. From 2001 to 2007, the EPU index was relatively low, and China’s grain import potential ratio was high; that is, China’s actual grain import value was closer to the fitted value. China implemented a series of tariff reduction measures after its WTO accession at the end of 2001, and EPU decreased, leading to the increase of grain imports[54] and the significant increase of import potential ratio. The EPU index decreased as China began to abolish agricultural taxes in 2006, and China’s grain import increased afterwards. The EPU index increased greatly with the outbreak of the world food crisis and financial crisis in 2008, which played a significant role in global trade collapse[55]. Many countries imposed restrictions on grain exports to ensure domestic grain supply, and China’s grain import potential ratio decreased significantly. After 2008, the EPU index showed significant upward trend, and China’s grain import potential ratio showed a significant downward trend. The EPU index rose sharply especially during the Sino-US trade war in 2018 and the outbreak of COVID-19 in 2019, resulting in remarkable decline in China’s grain import potential ratio. Therefore, the increase of EPU index led to the decrease of China’s grain imports and the decrease of import potential ratio and had a negative impact on the economic sustainability of China’s net grain imports.

   Secondly, the impact of EPU on China’s grain import potential ratio was time-varying. The overall change of the impulse response value of the whole sample shows that the negative impact of EPU on China’s grain import potential ratio reached the maximum in the second response period of all sample years (2001–2019), indicating that EPU had a significant negative impact on grain import potential in a short period (lag two periods), and then the negative impact gradually decreased to zero with the increase of response periods. In terms of the change of impulse response value in each year, the negative impact of EPU on the grain import potential ratio was the biggest in the second response period of 2019, with a value of −0.288, while the impact was relatively small in the second response period of 2005, with a value of only −0.242. This shows that the negative impact of EPU on China’s grain import potential ratio varies with time.

   (2) Impact of China’s EPU on Its Grain Trade Cost

   As seen in the impulse response results of the impact of EPU on China’s grain trade cost, a standard deviation impact of EPU random interference term had great positive
impact on China’s grain trade cost, which was remarkably time-varying, as shown in Figure 8b.

Firstly, the positive impact of EPU on China’s grain trade cost shows that when EPU increases, trade cost increases accordingly. China’s grain trade cost was the highest in 2001 and then decreased as EPU decreased after China’s WTO accession at the end of 2001. The outbreak of the world food crisis and financial crisis in 2008 led to higher EPU, and the world’s major grain export countries increased control of grain exports through export tariffs to ensure domestic supply. Consequently, China’s grain trade cost increased significantly. After 2011, China’s grain trade cost decreased as EPU decreased. From 2015 to 2017, EPU decreased with China’s RMB exchange rate mechanism reform, and trade cost declined accordingly. However, Sino–US trade conflict in 2018 and COVID-19 in 2019 led to the increase of EPU and the rise of China’s grain trade cost[33].

Secondly, the positive impact of EPU on China’s grain trade cost was time-varying. The overall change of the impulse response value of the whole sample shows that the positive impact of EPU on China’s grain trade cost reached the maximum in the third response period, which reflects that EPU had greater positive impact on grain trade cost in the long run (three lag periods). With the increase of response periods, this positive impact decreased to zero after the sixth period. In the third response period of 2008 and 2019, the positive impact of EPU on grain trade cost was relatively large, with the response value of 0.282 and 0.314, respectively; in the third response period of 2006, the positive impact of EPU was relatively small, with the response value of 0.262. This reflects that the positive impact of EPU on grain trade costs varies with time.

Therefore, EPU had a negative impact on the economic sustainability of China’s net grain imports. The rise of EPU index decreased China’s grain import potential ratio while it increased trade costs, which reduced the economic sustainability of China’s net grain imports.
Impact on trade cost

Figure 8. Impact of EPU on import potential ratio and trade cost.

2. Impact of China’s EPU on the Environmental Sustainability of Its Net Grain Imports
   As seen in the impulse response results of the impact of EPU on the changes of virtual land, virtual water, and embodied carbon emissions of China’s net grain imports, a standard deviation impact of the random interference term of EPU had a significant negative impact on the three indicators (Figure 9).
Firstly, EPU had a negative impact on virtual land, virtual water, and embodied carbon emissions imports. The decrease of EPU promoted the growth of China’s net grain imports, so it also had a positive impact on the import of virtual land, virtual water, and the reduction of carbon emissions. For example, EPU decreased during China’s RMB exchange rate system reform from 2015 to 2017, and virtual land, virtual water imports, and embodied carbon emissions increased significantly. In 2015, the substantial increase of China’s net grain imports, a result of the appreciation of the RMB to the Brazil Real and the Canadian Dollar and the growing soybean demand in Chinese market, led to a significant increase in virtual land imports, virtual water imports, and carbon emissions reduction. The decrease of China’s net grain imports in 2016 because of the deterioration of international commodity trade environment and the depreciation of the RMB to the USD, led to the decrease of virtual land imports, virtual water imports, and embodied carbon emissions. The Sino-US trade war in 2018 and the outbreak of COVID-19 in 2019 led to a sharp rise in the EPU index and to a sharp decline in virtual land, virtual water imports, and embodied carbon emissions in China’s net grain imports, and thus increased the environmental costs of agricultural production[56].

Secondly, the negative impacts of EPU on virtual land, water imports, and embodied carbon emissions were different in magnitude. EPU had the greatest negative impact on virtual water imports but had less impact on virtual land imports and embodied carbon emissions. The maximum negative response of virtual water imports to EPU impact was −0.422, while those of virtual land imports and embodied carbon emission were−0.195 and −0.208, respectively. The main reason for this difference is that grain is highly water-consuming, so the import of virtual water in grain imports is more significant compared with import of virtual land and the reduction of carbon.

Thirdly, the negative impact of EPU on China’s virtual land and water imports and embodied carbon emission was time-varying. It can be seen from the overall change of the impulse response value of the whole sample that the negative impact of EPU on the three factors reached the maximum value in the third response period and then the negative impact gradually decreased to zero with the increase of response periods.

Therefore, EPU has a negative impact on the environmental sustainability of China’s net grain imports. With the rise of the EPU index, virtual water and virtual land imports and embodied carbon emissions in China’s net grain imports decreases, which reduces the environmental sustainability of China’s net grain imports.
EPU has a very significant negative impact on the sustainable development of China’s net grain imports (Table 6). On the one hand, a higher EPU index leads to lower import potential ratio and higher trade cost. Therefore, EPU has a negative impact on the economic sustainability of China’s net grain imports. On the other hand, the rise of the EPU index also leads to a decrease of virtual land, virtual water imports, and embodied carbon emissions, so it reduces the environmental sustainability of China’s net grain imports. Therefore, the rise of EPU poses challenges to the sustainability of China’s net grain imports. With the rise of anti-globalization and protectionism, EPU will affect the sustainability of China’s net grain imports even more significantly. The Sino-US trade war, in particular, had a lasting and profound negative impact on the sustainability of China’s net grain imports. The outbreak of COVID-19 and its global spread in 2020 urged all countries to lay more emphasis on national food security, with emergency measures to restrict grain exports. Therefore, it is imperative for China to find countermeasures in the face of increasing EPU in order to promote the sustainability of China’s net grain imports and to ensure its food security.

| Sustainability | Indicators                  | Impact of EPU | Overall Evaluation                                      |
|----------------|-----------------------------|---------------|---------------------------------------------------------|
| Economic sustainability | Import potential ratio | Negative       | EPU has negative impact on both economic and environmental sustainability of China’s net grain imports. |
|                 | Trade cost                 | Positive      |                                                          |
|                 | Virtual land               | Negative      |                                                          |
| Environmental sustainability | Virtual water | Negative      |                                                          |
|                 | Embodied carbon emissions  | Negative      | a negative impact on the overall sustainability of China’s net grain imports. |

5. Conclusions and Implications

5.1. Conclusions

This study evaluated the sustainability of China’s net grain imports from both an economic and an environmental perspective through the estimation of its grain import potential ratio, trade cost, virtual land imports, virtual water imports, and embodied carbon emissions from 2001 to 2019. It analyzed the impact of the EPU index on these indicators with the help of the TVP-SV-VAR model, exploring the impact of EPU on the sustainable development of China’s net grain imports. The main conclusions are as follows. (1) Among the events included in EPU, China’s WTO accession, the outbreak of the world food crisis and financial crisis, the reform of China’s exchange rate system and the outbreak of Sino-US trade conflict can cause significant changes in the economic and environmental sustainability of China’s net grain imports. (2) From an economic perspective, EPU has a negative impact on the sustainability of China’s grain import. A higher EPU index leads to a low import potential ratio and higher trade costs, which harms the economic sustainability of China’s net grain imports. (3) Environmentally, the EPU index has a significant negative impact on environmental sustainability. It has a greater negative impact on virtual land and virtual water imports but less impact on embodied carbon emissions. The outbreak of Sino-US trade conflict, in particular, led to a remarkable increase in the environmental cost of grain production in China.

5.2. Implications

EPU significantly affects the sustainability of China’s grain trade. In recent years, the frequent occurrence of trade conflicts between China and the United States and the outbreak of COVID-19, in particular, have severely impacted the sustainability of China’s net grain imports. In order to make full use of the international market and resources to ensure domestic food security, release the pressure on the resources and environment of grain production, and meanwhile, avoid the severe impact of large grain imports on the domestic market, it is necessary for China to optimize its grain trading system and continuously improve grain production efficiency.
China should further optimize its grain trade policy, strengthen international cooperation, and promote the construction of a trade information platform so as to enhance the sustainability of China's net grain imports. First, China should further optimize its trade market structure and strengthen international cooperation. China’s grain imports are severely challenged by American trade policy and international trade protectionism, so the domestic grain market is facing enormous pressure. In order to ensure food security and stabilize the international supply of food, China should strengthen strategic cooperation with major grain export countries through trade consultation and should develop bilateral trade based on comparative advantages to stabilize cooperative relations. Secondly, China should optimize its grain trade system and straighten out the relationship between the participants in all aspects of grain trade. It is important for China to optimize the grain tariff quota system, relax the market self-regulation, weaken administrative factors, strengthen market supervision, and improve the efficiency of grain import and export customs. Thirdly, China’s agricultural products trade market faces increasing uncertainty given the growing trend of anti-globalization and trade protectionism. Therefore, China should accelerate the construction of a Customs grain trade big data platform by subdividing the types of grain products and unifying the data to enhance the reliability and availability of data. A data collection and analysis department should be established to analyze and forecast food security in the world and in China, and a supporting system of grain trade monitoring and early warning should also be set up.

Meanwhile, China should strive to improve domestic grain production efficiency and improve the utilization rate of agricultural resources to enhance international competitiveness. Advanced production and processing technology and management experience should also be introduced and applied by strengthening exchanges and cooperation with research institutions to improve grain yield. Improvement of the utilization rate of agricultural resources can be achieved through the application of advanced technologies. The efficiency of water utilization can be improved by strengthening the management of farmland soil moisture as well as through improving the efficiency of water management through the application of sprinkle irrigation, drip irrigation, and other more efficient irrigation technologies. China should strictly safeguard the area of cultivated land and should conduct intensive management of land to improve the efficiency of land utilization, for example, through the development of three-dimensional agriculture and inter-cropping. Meanwhile, it is also important to reduce the residue of harmful substances to improve land quality and productivity and to ensure the environmental sustainability of China’s grain production.

Author Contributions: Conceptualization, Y.L. and J.L.; methodology, J.L.; software, J.L.; validation, Y.L., J.L.; formal analysis, Y.L.; investigation, J.L.; resources, Y.L.; data curation, J.L.; writing—original draft preparation, Y.L., J.L.; writing—review and editing, Y.L., J.L.; visualization, Y.L.; supervision, J.L.; project administration, J.L.; funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Shandong Social Science Planning Project, grant number 19CYYJ16.

Conflicts of Interest: The authors declare no conflict of interest.

References
1. Huang, J.; Wei, W.; Cui, Q.; Xie, W. The prospects for China’s food security and imports: Will China starve the world via imports? J. Integr. Agric. 2017, 16, 2933–2944.
2. Jiang, S.; Wang, J.; Zhao, Y.; Shang, Y.; Gao, X.; Li, H.; Wang, Q.; Zhu, Y. Sustainability of water resources for agriculture considering grain production, trade and consumption in China from 2004 to 2013. J. Clean. Prod. 2017, 149, 1210–1218.
3. He, G.; Zhao, Y.; Wang, L.; Jiang, S.; Zhu, Y. China’s food security challenge: Effects of food habit changes on requirements for arable land and water. J. Clean. Prod. 2019, 229, 739–750.
4. Yang, H.; Wang, L.; Zehnder, A.J.B. Water scarcity and food trade in the Southern and Eastern Mediterranean countries. *Food Policy* **2007**, *32*, 585–605.

5. Wang, J.; Li, Y.; Huang, J.; Yan, T.; Sun, T. Growing water scarcity, food security and government responses in China. *Glob. Food Secur.* **2017**, *14*, 9–17.

6. Piao, S.; Ciais, P.; Huang, Y.; Shen, Z.; Peng, Z.; Li, J.; Zhou, L.; Liu, H.; Ma, Y.; Ding, Y.; et al. The impacts of climate change on water resources and agriculture in China. *Nature* **2010**, *467*, 43–51.

7. Dalin, C.; Hanasaki, N.; Qiu, H.; Mauzerall, D.L.; Rodriguez, I. Water resources transfers through Chinese interprovincial and foreign food trade. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 9774–9779.

8. Grossman, G.M.; Krueger, A.B. *Environmental Impacts of a North American Free Trade Agreement*; NBER Working Papers: Cambridge, MA, USA, 1991; No. W3914.

9. International Chamber of Commerce (ICC). Global Trade: Securing Future Growth. International Chamber of Commerce, 2018.

10. Armstrong, S. *Measuring Trade and Trade Potential: A Survey*; Asia Pacific Economic Papers: Canberra, Australia, 2007; No. 368.

11. Egger, P. An Econometric view on the estimation of Gravity Models and the calculation of trade potentials. *World Econ.* **2002**, *25*, 297–312.

12. Rennini, V.R.; Kar, A.; Jha, G.K.; Kumar, P.; Burman, R.R.; Praveen, K.V. Agricultural trade potential between India and ASEAN: An application of gravity model. *Agric. Econ. Res. Rev.* **2017**, *30*, 105–113.

13. Jagdambe, S.; Kannan, E. Effects of ASEAN-India Free Trade Agreement on agricultural trade: The gravity model approach. *World Dev. Perspect.* **2020**, *19*, 100122.

14. Butter, F.A.G.D.; Mosch, R.H.J. *Trade, Trust and Transaction Costs*; Tinbergen Institute Discussion Paper: Amsterdam, Netherlands, 2003; No.03-082/3.

15. Anderson, J.E.; van Wincoop, E. Gravity with gravitas: A solution to the border puzzle. *Am. Econ. Rev.* **2003**, *93*, 170–192.

16. Jacks, D.S.; Meissner, C.M.; Novy, D. Trade costs, 1870–2000. *Am. Econ. Rev. Pap. Proc.* **2008**, *98*, 529–554.

17. Tuninetti, M.; Luca, R.; Laio, F. Charting out the future agricultural trade and its impact on water resources. *Sci. Total Environ.* **2020**, *714*, 136627.

18. Zhang, Y.; Zhang, J.; Tang, G.; Chen, M.; Wang, L. Virtual water flows in the international trade of agricultural products of China. *Sci. Total Environ.* **2016**, *557–559*, 1–11.

19. Zhang, Y.; Zhang, J.; Wang, C.; Cao, J.; Liu, Z.; Wang, L. China and Trans-Pacific Partnership Agreement countries: Estimation of the virtual water trade of agricultural products. *J. Clean. Prod.* **2017**, *140*, 1493–1503.

20. Lamastra, L.; Miglietta, P.P.; Toma, P.; De Leo, F.; Massari, S. Virtual water trade of agri-food products: Evidence from Italian-Chinese relations. *Sci. Total Environ.* **2017**, *599–600*, 474–482.

21. Qiang, W.; Niu, S.; Liu, A.; Kastner, T.; Bie, Q.; Wang, X.; Cheng, S. Trends in global virtual land trade in relation to agricultural products. *Land Use Policy* **2020**, *92*, 104439.

22. Qiang, W.; Liu, A.; Cheng, S.; Kastner, T.; Xie, G. Agricultural trade and virtual land use: The case of China’s crop trade. *Land Use Policy* **2013**, *33*, 141–150.

23. Taherzadeh, O.; Caro, D. Drivers of water and land use embodied in international soybean trade. *J. Clean. Prod.* **2019**, *223*, 83–93.

24. Grosso, S.J.D.; Mosier, A.R.; Parton, W.J.; Ojima, D.S. *DAYCENT* model analysis of past and contemporary soil N2O and net greenhouse gas flux for major crops in the USA. *Soil Tillage Res.* **2005**, *83*, 9–24.

25. Niu, B.; Peng, S.; Li, C.; Liang, Q.; Li, X.; Wang, Z. Nexus of embodied land use and greenhouse gas emissions in global agricultural trade: A quasi-input–output analysis. *J. Clean. Prod.* **2020**, *267*, 122067.

26. Escobar, N.; Tizado, E.J.; zu Ermingassen, E.K.H.J.; Löfgren, P.; Förner, J.; Godar, J. Spatially-explicit footprints of agricultural commodities: Mapping carbon emissions embodied in Brazil’s soy exports. *Glob. Environ. Chang.* **2020**, *62*, 102067.

27. Gülen, H.; Ion, M. Policy uncertainty and corporate investment. *Rev. Finan. Stud.* **2016**, *29*, 523–564.

28. Baker, S.; Bloom, N.; Davis, S. Measuring economic policy uncertainty. *Quart. J. of Econ.* **2016**, *131*, 1593–1636.

29. Fontaine, I.; Didier, L.; Razafindravaosolonirina, J. Foreign policy uncertainty shocks and US macroeconomic activity: Evidence from China. *Econ. Lett.* **2017**, *155*, 121–125.

30. Meinen, P.; Roehe, O. On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area. *Eur. Econ. Rev.* **2017**, *92*, 161–179.

31. Su, R.; Du, J.; Shahzad, F.; Long, X. Unveiling the Effect of Mean and Volatility Spillover between the United States Economic Policy Uncertainty and WTI Crude Oil Price. *Sustainability* **2020**, *12*, 6662, doi:10.3390/su12166662.

32. Song, Y.; Hao, F.; Hao, X.; Gozgor, G. Economic Policy Uncertainty, Outward Foreign Direct Investments, and Green Total Factor Productivity: Evidence from Firm-Level Data in China. *Sustainability* **2021**, *13*, 2393, doi:10.3390/su13042393.

33. Novy, D.; Taylor, A.M. *Trade and Uncertainty*; NBER Working Paper: London, UK, 2014; No. 1266.

34. Handley, K. Exporting under trade policy uncertainty: Theory and evidence. *J. Int. Econ.* **2014**, *91*, 50–66.

35. Limao, N.; Maggi, G. Uncertainty and trade agreements. *Am. Econ. J. Microecon.* **2015**, *4*, 1–20.

36. Greenland, A.; Ion, M.; Lopresti, J. *Exports, Investment and Policy Uncertainty*. Canadian Journal of Economics. 2019,52, 1248-1288.

37. Udmale, P.; Pal, I.; Szabo, S.; Pramanik, M.; Large, A. Global food security in the context of COVID-19: A scenario-based exploratory analysis. *Prog. Disaster Sci.* **2020**, *7*, 100120.
38. Balwinder, S.; Shirsath, P.B.; Jat, M.L.; McDonald, A.J.; Srivastava, A.K.; Craufurd, P.; Rana, D.S.; Singh, A.K.; Chaudhari, S.K.; Sharma, P.C.; et al. Agricultural labor, COVID-19, and potential implications for food security and air quality in the breadbasket of India. *Agric. Syst.* 2020, 185, 102954.

39. Zhou, J.-H.; Han, F.; Li, K.; Wang, Y. Vegetable production under COVID-19 pandemic in China: An analysis based on the data of 526 households. *J. Integr. Agric.* 2020, 19, 2854–2865.

40. Wang, H.H.; Hao, N. Panic buying? Food hoarding during the pandemic period with city lockdown. *J. Integr. Agric.* 2020, 19, 2854–2865.

41. Yao, H.; Zuo, X.; Zuo, D.; Lin, H.; Huang, X.; Zang, C. Study on soybean potential productivity and food security in China under the influence of COVID-19 outbreak. *Geogr. Sustain.* 2020, 1, 163–171.

42. Huang, J.; Yang, J.; Rozelle, S. China’s agriculture: Drivers of change and implications for China and the rest of world. *Agric. Econ.* 2010, 41, 47–55.

43. Li, D.; Zeng, J. The challenges facing the food security of China under the New Normal economic situation. *Issues Agric. Econ.* 2015, 5, 42–47+110. (In Chinese)

44. Mao, X.; Kong, X. Reshaping the future of food security in China. *J. Nanjing Agric. Univ. (Soc. Sci. Edition)* 2019, 19, 142–150+168. (In Chinese)

45. Novy, D. Gravity redux: Measuring international trade costs with panel data. *Econ. Inq.* 2013, 51, 101-121.

46. Tinbergen, J. *Shaping the World Economy: Suggestions for an International Economic Policy*; The Twentieth Century Fund: New York, NY, USA, 1962.

47. Baek, J. Does the exchange rate matter to bilateral trade between Korea and Japan? Evidence from commodity trade data. *Econ. Modeling* 2013, 30, 856–862.

48. Daniloska, N. International trade with food and agricultural products: Aspect of Nontariff Barriers. *Econ. Dev.* 2015, 1–2, 163–174.

49. West, T.O.; Marland, G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United States. *Agric. Ecosyst. Environ.* 2002, 91, 217–232.

50. Dubey, A.; Lal, R. Carbon footprint and sustainability of agricultural production system in Punjab, India and Ohio, USA. *J. Crop Improv.* 2009, 23, 332–350.

51. Nakajima, J. Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications. *IMES Discuss. Paper Ser.* 2011, 29, 107–142.

52. Wei, S. *Intra-National Versus International Trade: How Stubborn are Nations in Global Integration*; NBER Working Paper: Cambridge, MA, USA, 1996; No. 5531.

53. Huang, Y.; Luk, P. Measuring economic policy uncertainty in China. *China Econ. Rev.* 2020, 59, 101367.

54. Sun, Z.; Li, X. Puzzle of China’s Grain Trade Deficit: Variety, price and quantity. *J. Int. Trade.* 2018, 9, 9–24. (In Chinese)

55. Carballo, J.; Handley, K.; Lim, N. *Economic and Policy Uncertainty: Export Dynamics and the Value of Agreements*; NBER Working Paper: Cambridge, MA, USA, 2018; No. 24368.

56. He, R.; Zhu, D.; Chen, X.; Cao, Y.; Chen, Y.; Wang, X. How the trade barrier changes environmental costs of agricultural production: An implication derived from China’s demand for soybean caused by the US-China trade war. *J. Clean. Prod.* 2019, 227, 578–588.