Towards a Healthy Agri-food System in Rural China: Inequality, Digitalization, and Environmental Policy

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Summary

Amid the dual global challenges of malnutrition and environmental degradation, promoting a shift in the agri-food system towards health and sustainability has become a key priority for achieving public health and environmental goals. As the largest developing economy, China has undergone rapid changes in food consumption over the past four decades. This transition significantly improves the population's overall nutritional status, but it also gives rise to growing public health concerns, including increasing rates of overweight, obesity, and diet-related chronic diseases. At the same time, evolving food consumption patterns contribute to mounting environmental pressures, particularly in sectors that are water- and carbon-intensive. These challenges are especially pronounced in rural areas, where limited infrastructure, low income levels, and reduced access to diverse and nutritious foods intensify the dual burden of dietary inadequacy and environmental stress.

This dissertation examines the drivers of the agri-food system in rural China. It mainly evaluates their impacts on a healthy agri-food system through four interrelated research topics, with a particular focus on income inequality, digitalisation, and environmental policy. Specifically: (i) using data from the 2015 China Health and Nutrition Survey (CHNS), it applies ordinary least squares (OLS) regression to assess the effect of income inequality on body mass index (BMI), and employs a multinomial logit model to analyse its association with underweight, overweight, and obesity (Chapter 2); (ii) drawing on panel data from the CHNS spanning 2004 to 2015, it adopts an instrumental variable approach to estimate the impact of internet use on dietary quality, overweight and obesity, as well as the risks of chronic diseases such as diabetes and hypertension (Chapter 3); (iii)using panel data form CHNS spaning 2004 to 2011, it further employs an instrumental variable model to estimate the effect of internet use on the food carbon and water

footprints (Chapter 4); and (iv) Based on the panel data of 140 counties in Sichuan province, China, from 2002 to 2018, we examined the causal effect of Forest Farm Carbon Sink (FFCS) project on agricultural total factor productivity (TFP) (Chapter 5).

Chapter 2 constructs three household-level indices of income inequality and estimates the impact of income inequality on nutritional outcomes. In contrast to previous studies, the results reveal that as per capita household income increases rapidly, the relationship between income and BMI shifts from positive to negative. Moreover, rising income inequality significantly elevates the risk of overweight and obesity among low-income groups. These findings highlight the importance of reducing income inequality to mitigate the adverse health effects associated with the transition in food consumption in rural China.

Chapter 3 finds that internet use improves rural residents' dietary knowledge, thereby enhancing overall dietary quality. However, it also increases the risk of overweight and obesity, primarily due to a significant decline in physical activity associated with increased internet use. Interestingly, while internet use is positively associated with higher self-rated health scores, it simultaneously elevates the risk of chronic diseases such as diabetes and hypertension. This discrepancy suggests a potential lack of awareness among rural residents regarding the long-term health risks of chronic conditions. These findings highlight the dual nature of digital transformation in shaping food consumption and health outcomes. Policymakers should therefore pay closer attention to its unintended negative consequences, particularly in rural contexts.

Chapter 4 reveals that internet use significantly reduces both the food carbon footprint and the food water footprint by 18.1% and 10.6%, respectively. A decline in the consumption of animal-based foods such as pork and eggs mainly drives this reduction. Further heterogeneity analysis reveals that the effect of internet use on promoting sustainable food consumption is more pronounced among younger individuals and those from high-income groups. These findings suggest that digital platforms can serve as an effective tool to guide dietary shifts by encouraging reduced consumption of animal-based foods and greater intake of plant-based alternatives. Moreover, increasing the income of low-income households through non-digital means also helps foster sustainable food consumption.

Chapter 5 shows that implementing the FFCS policy not only absorbs carbon dioxide to mitigate global warming but also contributes to agricultural TFP growth. Specifically, FFCS can increase agricultural TFP by 1.7% to 2.4%. Health, saving, and industrial structure are the important channels through which FFCS projects affect agricultural TFP. However, we also find that the effect of FFCS projects on agricultural TFP is likely to be one-off rather than sustainable. Besides, the positive effect of international projects on agricultural TFP is greater than that of domestic projects.

In summary, this thesis systematically examines how income inequality, digitalisation, and environmental policy shape the healthy agri-food system in rural China. The findings provide valuable insights for developing countries undergoing rapid socio-economic change in their pursuit of healthy and sustainable agri-food system transitions.

Zusammenfassung

Vor dem Hintergrund der zeitgleich bestehenden globalen Herausforderungen von Mangelernährung und Umweltverschmutzung gewinnt die Förderung einer Transformation des Agrar- und Ernährungssystems hin zu einer gesünderen und nachhaltigeren Ernährung zentrale Bedeutung, um sowohl gesundheits- als auch umweltpolitische Ziele zu erreichen. Als größte aufstrebende Volkswirtschaft hat China in den letzten vier Jahrzehnten einen rasanten Wandel im Hinblick auf die Ernährungsgewohnheiten seiner Bevölkerung erfahren. Dieser Wandel hat zwar zu einer deutlichen Verbesserung des allgemeinen Ernährungszustands der Bevölkerung beigetragen, zugleich jedoch zunehmende gesundheitliche Herausforderungen hervorgerufen, darunter steigende Prävalenzen von Übergewicht, Adipositas sowie ernährungsbedingten chronischen Erkrankungen. Gleichzeitig nehmen die Umweltbelastungen – insbesondere durch Produktionssektoren mit hohem Wasserverbrauch und CO2-Ausstoß – infolge der veränderten Ernährungsmuster zu. Besonders ausgeprägt treten diese Problemlagen in ländlichen Regionen zutage, wo begrenzte Infrastrukturen, niedrige Einkommensniveaus und ein eingeschränkter Zugang zu vielfältigen und nährstoffreichen Lebensmitteln die gleichzeitige Herausforderung von Mangelernährung und ökologischer Belastung zusätzlich verschärfen.

Diese Dissertation analysiert die Triebkräfte des Wandels im Agrar- und Ernährungssystem im ländlichen China und bewertet dessen gesundheitlichen und ökologischen Auswirkungen anhand von vier miteinander verknüpften Forschungsthemen, mit besonderem Fokus auf Einkommensungleichheiten, Digitalisierung und Umweltpolitik. Konkret: (i) Auf Basis der Daten des China Health and Nutrition Survey (CHNS) von 2015 wird ein OLS-Modell zur Schätzung des Einflusses von Ungleichheiten der Einkommen auf den Body-Mass-Index (BMI) verwendet, ergänzt durch ein multinomiales Logit-Modell zur Analyse von Untergewicht, Übergewicht und

Adipositas (Kapitel 2); (ii) mit CHNS-Daten von 2004 bis 2015 wird ein Instrumentvariablenansatz angewendet, um die Auswirkungen der Internetnutzung auf Ernährungsqualität, Übergewicht, Adipositas sowie das Risiko chronischer Erkrankungen wie Diabetes und Bluthochdruck zu schätzen (Kapitel 3); (iii) abschließend wird mit Hilfe der CHNS-Daten und einem Instrumentvariablenmodell der Effekt der Internetnutzung auf den CO2- sowie den Wasserfußabdruck des Lebensmittelkonsums geschätzt (Kapitel 4); (iv) basierend auf Paneldaten von 140 Landkreisen in der chinesischen Provinz Sichuan für den Zeitraum 2002 bis 2018 untersuchen wir in Kapitel 5 den kausalen Effekt des Forest-Farm-Carbon-Sink-(FFCS)-Projekts auf die totale Faktorproduktivität (TFP) in der Landwirtschaft (Kapitel 5).

Kapitel 2 konstruiert drei Einkommensungleichheitsindizes auf Haushaltsebene und untersucht deren Einfluss auf die Auswirkungen der Ernährungsweise. Im Gegensatz zu früheren Studien zeigen die Ergebnisse, dass sich mit dem raschen Anstieg des Pro-Kopf-Haushaltseinkommens der Zusammenhang zwischen Einkommen und BMI von positiv zu negativ verschiebt. Zudem erhöht zunehmende Ungleichheit der Einkommen das Risiko für Übergewicht und Adipositas insbesondere bei einkommensschwachen Haushalten deutlich. Diese Befunde unterstreichen die Bedeutung der Verringerung von Einkommensungleichheit als zentrale Maßnahme zur Abmilderung negativer gesundheitlicher Folgen des Ernährungstransformationsprozesses im ländlichen China.

Kapitel 3 zeigt, dass die Internetnutzung das Wissen der Landbevölkerung im Hinblick auf eine gesunde und nachhaltige Ernährungsweise verbessert und somit die allgemeine Ernährungsqualität steigert. Gleichzeitig erhöht sie jedoch das Risiko für Übergewicht und Adipositas, was vor allem auf den Rückgang körperlicher Aktivität im Zuge der Digitalisierung zurückzuführen ist. Auffällig ist zudem, dass Internetnutzung zwar mit einer höheren subjektiven Bewertung der Ziele im

Hinblick auf die eigene Gesundheit verbunden ist, jedoch gleichzeitig das Risiko für chronische Krankheiten wie Diabetes und Bluthochdruck erhöht. Diese Diskrepanz weist auf ein mögliches Defizit im Bewusstsein für langfristige Gesundheitsrisiken hin. Die Ergebnisse verdeutlichen die ambivalente Rolle des digitalen Wandels im Bereich Ernährung und Gesundheit. Daher sollte die Politik insbesondere im ländlichen Raum vor allem den negativen Auswirkungen mehr Aufmerksamkeit schenken.

Kapitel 4 zeigt, dass die Internetnutzung den CO2- und den Wasserfußabdruck von Lebensmitteln deutlich reduziert, und zwar um 18,1 % beziehungsweise 10,6 %. Diese Verringerung beruht vor allem auf einem geringeren Konsum tierischer Produkte wie Schweinefleisch und Eiern. Die Heterogenitätsanalyse verdeutlicht, dass dieser Effekt bei jüngeren Menschen und einkommensstarken Gruppen besonders ausgeprägt ist. Die Ergebnisse legen nahe, dass digitale Plattformen ein effektives Instrument sind, um Ernährungsumstellungen zu fördern, indem sie den Konsum tierischer Lebensmittel reduzieren und den Verzehr pflanzlicher Alternativen steigern. Zudem trägt die Einkommenssteigerung einkommensschwacher Haushalte durch nicht-digitale Maßnahmen ebenfalls zur Förderung eines nachhaltigen Lebensmittelkonsums bei.

Kapitel 5 zeigt, dass die Umsetzung der FFCS-Politik nicht nur zur Bindung von Kohlendioxid und damit zur Abschwächung der globalen Erwärmung beiträgt, sondern auch das Wachstum der totalen Faktorproduktivität (TFP) in der Landwirtschaft fördert. Konkret kann FFCS die landwirtschaftliche TFP um 1,7 % bis 2,4 % steigern. Gesundheit, Ersparnisse und die industrielle Struktur stellen zentrale Kanäle dar, über die FFCS-Projekte die TFP in der Landwirtschaft beeinflussen. Allerdings zeigt sich, dass die Auswirkungen von FFCS-Projekten auf die landwirtschaftliche TFP eher einmalig als dauerhaft sind. Zudem sind die positiven Effekte internationaler Projekte auf die landwirtschaftliche TFP stärker ausgeprägt als jene inländischer Projekte.

Zusammenfassend untersucht diese Arbeit systematisch, wie Einkommensungleichheit, Digitalisierung und Umweltpolitik die Entwicklung eines gesunden Agrar- und Ernährungssystems im ländlichen China prägen. Die Ergebnisse liefern wertvolle Erkenntnisse für Entwicklungsländer, die sich in einem raschen sozioökonomischen Wandel befinden und eine gesunde sowie nachhaltige Transformation ihrer Agrar- und Ernährungssysteme anstreben

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ATE	Average Treatment Effects
BMI	Body Mass Index
CHNS	China Health and Nutrition Survey
CINIC	China Internet Network Information Center
CNY	Chinese Yuan Renminbi
DDS	Dietary Diversity Score
DGC	Dietary Guidelines for Chinese
FAO	Food and Agriculture Organization
FFCS	Forest Farm Carbon Sink
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GNI	Gross National Income
HEI	Healthy Eating Index
IV	Instrumental Variables
OLS	Ordinary Least Squares
SDGs	Sustainable Development Goals
TFP	Total Factor Productivity
WHO	World Health Organization
WTO	World Trade Organization

Chapter 1 Introduction

1.1 Problem statements and motivations

In the 21st century, malnutrition and environmental degradation have emerged as two significant global challenges in the transition toward a healthy agri-food system. Malnutrition extends beyond hunger to include a broad spectrum of nutritional imbalances, ranging from undernutrition to overnutrition. According to the 2020 Global Burden of Disease Study, more than 2 billion people worldwide experience undernutrition, while approximately 40% of adults and 20% of children are overweight or obese (GBD 2020 Risk Factors Collaborators, 2020). At the same time, food production and consumption are estimated to contribute 25% to 30% of anthropogenic greenhouse gas emissions, playing a significant role in biodiversity loss, freshwater depletion, and land system change (Crippa et al., 2021; Willett et al., 2019). In this context, establishing a healthy agri-food system has increasingly been recognized as a key strategy for improving public health and achieving multiple Sustainable Development Goals (SDGs).

In China, as in many other developing countries, food consumption has undergone profound changes over the past few decades. This transition is characterized by increased intake of dietary fats, high-calorie sweeteners, and animal products, as well as a growing reliance on processed foods (Chen et al., 2022; Cui et al., 2023). Prior to the implementation of the Reform and Opening-up policy in 1978, undernutrition and insufficient food supply were the primary nutritional challenges facing the Chinese population. During this period, average per capita cereal consumption remained below 150 kilograms annually, while meat consumption was less than 15 kilograms. The overall food supply fell short of even basic sustenance and clothing needs. As of 1978, the average daily per capita energy intake remains below 2,100 kilocalories—the minimum level recommended by the Chinese Nutrition Society for basic nutritional needs. Grain constitutes the primary source of dietary intake, with per capita consumption significantly exceeding that of all other food categories combined. The changes in food consumption among Chinese adults from 1961 to 2020 are shown in Figure 1.1.

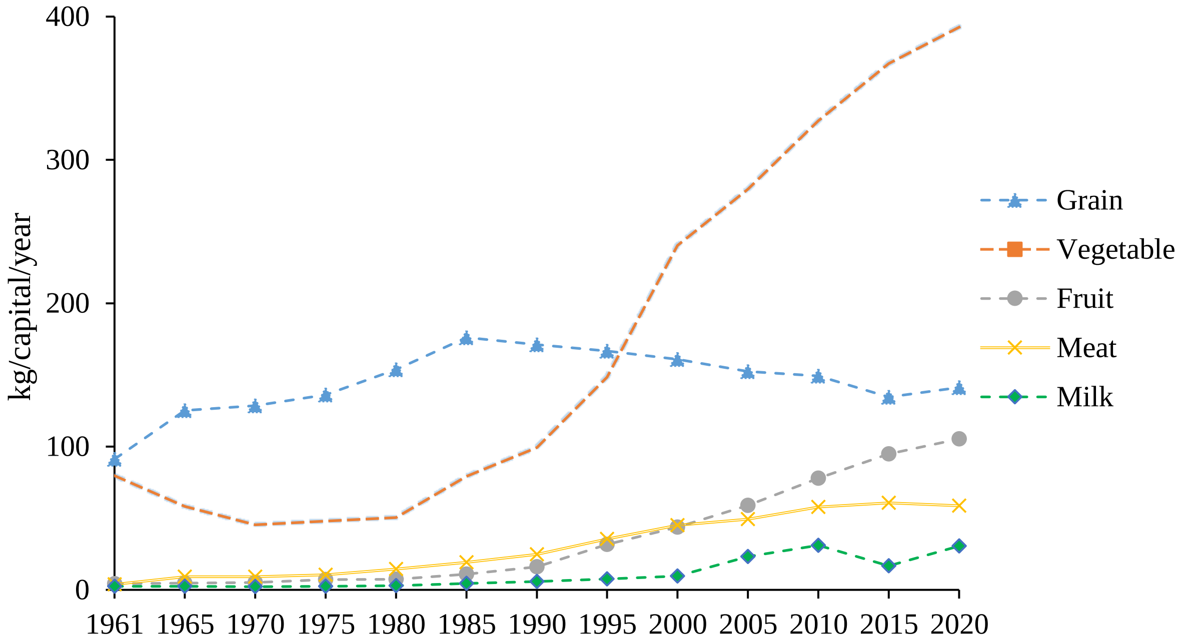

Figure 1.1: Changes in food consumption among Chinese adults from 1961 to 2020[1]

Data source: The Food and Agriculture Organization (**https://www.fao.org/faostat/en/#data**)

Between 1978 and 2000, food consumption in China increased substantially as income and living standards improved. Per capita grain consumption peaked in the 1980s. The consumption of vegetables and fruits grows by 2.8 and 4.8 times, while meat and dairy consumption increases by 2.2 and 1.9 times. Nutrient intake also improves steadily. By the mid-1980s, average daily per capita energy intake had surpassed 2,223 kilocalories, meeting the Food and Agriculture Organization's (FAO) minimum standard and marking a significant milestone in achieving basic

[1] The food consumption refers to food available for human consumption and may differ slightly from the actual amount consumed by individuals. For example, it includes a portion of food waste that is not actually eaten.

food security in China. In 2001, China joined the World Trade Organization (WTO), which expanded the openness of its agricultural markets and accelerated changes in food consumption. Staple food consumption, such as grains, continues to decline, while intake of high-protein, nutrient-rich foods, particularly meat, increases.

Changes in food consumption patterns in China present both opportunities and challenges. On the one hand, increased food availability improves the population's nutritional status. According to the FAO, the prevalence of undernourishment in China decreased from 24% in the 1990s to less than 2.5% by 2020 (Huang & Tian,2019). On the other hand, rising consumption of high-calorie and processed foods is closely linked to the growing burden of non-communicable diseases, including overweight, obesity, and diabetes. Current data show that over half of Chinese residents are overweight or obese, with overweight and obesity rates reaching 34.3% and 16.4%, respectively (Ren et al.,2021; Ren et al.,2019). Moreover, the Global Burden of Disease (GBD) study identifies dietary risk factors as the leading cause of death in China. In 2017, poor diet accounted for 3.1 million deaths, surpassing hypertension, which causes 2.5 million deaths (Fang et al., 2023). Compared to urban areas, rural regions face additional challenges, including lower incomes, weaker infrastructure, and limited access to diverse food and markets. In this context, identifying the drivers of food consumption transition, improving the quality of food intake, and reducing the health risks associated with poor diets—particularly in rural areas—emerge as urgent public health priorities for both researchers and policymakers.

This shift in food consumption also poses significant ecological challenges. Between 1980 and 2020, per capita grain intake decreased by 8.2%, while meat and vegetable consumption increased by 302.1% and 678.9%, respectively. Since grain foods generally have lower carbon and water footprints than animal-based products, the growing demand for meat poses a serious threat to

China's carbon-reduction goals (Hu et al., 2022; Xiong et al., 2020). At the same time, China faces severe water scarcity, with per capita water resources at only 28% of the global average, ranking it among the 13 most water-stressed countries. Although vegetables and fruits are essential for a healthy diet, their water footprint is considerably higher than that of many staple foods, adding further pressure on limited water resources. Evidence shows that between 1961 and 2017, China's food-related water and carbon footprints nearly tripled (Heller & Keoleian, 2015; Vermeulen et al., 2012). These environmental burdens are particularly pronounced in rural areas, where diets often either lack essential micronutrients or generate disproportionately high environmental costs (Asvatourian et al., 2018; Xiong et al., 2020). As a result, rural China faces a dual burden of dietary health risks and environmental stress, underscoring the urgent need for effective, targeted policy responses to mitigate the associated social and health impacts.

1.2 Literature review and research gaps

Existing research on food consumption transformation in rural China has mainly focused on nutritional and health outcomes, with particular attention to three key aspects. First, trends in food consumption indicate that total protein and fat intake among rural residents have increased substantially (Liu et al., 2020; He et al., 2019). However, dietary imbalances remain pronounced, and micronutrient deficiencies are still widespread (Liu et al., 2020; He et al., 2019). Second, scholars have examined the relationship between dietary changes and chronic disease risks (Wang et al., 2012; Yu et al., 2021). Evidence suggests that excessive carbohydrate intake is a major contributor to obesity and overweight in China (Liu et al., 2020; Yu et al., 2021), while rising consumption of animal-based foods and sugar-sweetened beverages has also been positively associated with health risks such as overweight, obesity, and hypertension (Zhang et al., 2018; Wang et al., 2012). Third, differences in dietary and nutritional outcomes across socio-economic groups have been highlighted (Shi et al., 2021; Ren et al., 2019). Factors such as income, education, age, digitalization, and dietary culture significantly shape individual food choices and nutritional intake, thereby influencing nutritional health outcomes (Shi et al., 2021; Ren et al., 2021).

To promote nutritional and health goals, researchers have developed a range of indices based on dietary guidelines to assess diet quality and guide individuals in improving their nutritional status (Patterson et al., 1994; Haines et al., 1999; Liu et al., 2020). The United States Department of Agriculture (USDA), for instance, introduced the Healthy Eating Index (HEI) based on the U.S. Dietary Guidelines (Patterson et al., 1994). In 1994, Patterson et al. proposed the Dietary Quality Index (DQI), which was later revised by Haines et al. in 1999 to reflect the updated guidelines, resulting in the DQI-R (Haines et al., 1999). The DQI-R consists of ten components, including separate measures for dietary diversity and dietary adequacy (Haines et al., 1999). Each component is scored from 0 to 10, with a maximum total score of 100, where higher scores indicate closer adherence to dietary recommendations (Haines et al., 1999; Liu et al., 2020). It is important to note that dietary consumption is powerfully shaped by regional habits and socio-economic changes, making it both region-specific and dynamic (Ren et al., 2019; Shi et al., 2021). In China, several indices have been developed based on the Dietary Guidelines for Chinese Residents (DGC) and the Chinese Food Pagoda (CFP), such as the Chinese Dietary Balance Index (DBI), the Chinese Dietary Quality Index (DQI), the Chinese Food Pagoda Score (CFPS), and the Chinese Healthy Eating Index (CHEI) (Liu et al., 2020; Shi et al., 2021). Increasingly, studies highlight that healthy dietary patterns should not only promote human health but also consider environmental sustainability (Zamani et al., 2018; Salahuddin et al., 2016). Against this backdrop, environmental footprints are also widely used to evaluate the environmental health impacts of food consumption transitions (Zhang et al., 2019a; Zamani et al., 2018). Besides, to address climate change driven by shifts in food consumption patterns, Chinese policymakers also introduced a range of environmental policies aimed at achieving the ‘dual carbon’ targets: reaching peak carbon emissions by 2030 and attaining carbon neutrality by 2060.” These policies may also influence the allocation of agricultural resources, such as land, labor, employment patterns, and income distribution, and in turn affect the transformation of the agri-food systems.

Regarding the driving factors of healthy agri-food systems in rural China, existing studies mainly emphasize the roles of income and urbanization in shaping food consumption and health outcomes (Huang & Tian, 2019; Ren et al., 2019). Evidence shows that the income elasticity of animal products such as milk, meat, and aquatic products is relatively high, whereas that of staple foods like coarse grains and starches is small or even negative (Huang & Tian, 2019). Consequently, low-income groups tend to rely on staple foods as the most cost-effective source of calories (Ren et al., 2019). As income rises, however, consumers pay increasing attention to attributes beyond nutrition, including appearance, taste, social status, perceived value, smell, and degree of processing (Tian & Yu, 2015). Since healthier foods are generally more expensive, low-income populations are more likely to adopt unhealthy options, a pattern also observed in developed countries (Ren et al., 2019; Shi et al., 2021). Research further indicates that income influences health through five channels: nutrient intake, dietary diversity, nutritional knowledge, food preferences, and dining out (Ren et al., 2019; Ren et al., 2021). Urbanization also plays an important role, as urban residents have greater access to markets and a wider range of food choices (Ren et al., 2021; Smart et al., 2020). Moreover, interactions among individuals with diverse dietary cultures during urbanization may shift food preferences, thereby driving nutritional transformation alongside urban development (Smart et al., 2020; Wang et al., 2016).

However, the existing literature has largely overlooked the impact of income inequality on food consumption and nutritional health (Ren et al., 2019; Ren et al., 2021). Over the past few decades, China has achieved remarkable economic growth, but rising concerns over income disparities have accompanied this progress (Huang & Tian, 2019). Estimates from the World Bank and China's National Bureau of Statistics indicate that the Gini coefficient increased from 0.28 in 1981 to 0.49 in 2008, remaining well above the internationally recognized warning threshold of 0.4 (Liu et al., 2021). Growing income inequality not only restricts low-income groups' access to goods and services but may also contribute to psychological stress and social exclusion, potentially undermining health outcomes (Ren et al., 2019; Shi et al., 2021). The Chinese government has acknowledged the risks posed by income inequality, particularly in rural areas (Ren et al., 2019). It has implemented policies to mitigate these disparities, such as the national poverty alleviation program that lifted the entire population out of absolute poverty by 2021 (Liu et al., 2021). Nevertheless, income inequality is expected to remain a persistent challenge for rural development in China (Ren et al., 2019). Consequently, it is crucial for both policymakers and rural residents to carefully consider the effects of income inequality on nutrition and health (Shi et al., 2021).

Researchers have also examined the impact of digitalization on the transformation of food consumption (Shen et al., 2023; Min et al., 2021). Internet use can improve food accessibility by enabling residents to obtain products that are unavailable in nearby supermarkets (Shen et al., 2023). It can also reduce transaction costs in agricultural markets, facilitate farmers' market participation, and thereby enhance consumers' food affordability (Min et al., 2021; Shen et al., 2023). Importantly, the Internet serves as a significant channel for accessing food and nutrition information, which can further improve consumers' dietary knowledge (Min et al., 2021; Shen et al., 2023). These changes may contribute to healthier food consumption patterns among rural residents (Min et al., 2021). However, existing studies often overlook the potential adverse effects of Internet use on health (Wang et al., 2012; Min et al., 2021). For example, excessive Internet use may promote sedentary behavior and reduce time spent outdoors, increasing the risk of overweight and obesity (Wang et al., 2012; Min et al., 2021). Physical activity is a key means of maintaining calorie balance and overall health, and reduced exercise time can undermine these benefits (Min et al., 2021). Several studies have investigated the effects of Internet use on dietary quality (Shen et al., 2023). However, findings remain mixed, and high-quality research specifically addressing the impact on nutritional health in rural China is still limited (Shen et al., 2023).

A healthy agri-food system should also consider its environmental impact (Zamani et al., 2018; Salahuddin et al., 2016). Overall, the literature shows that population growth, urbanization, and rising incomes have shifted diets from primarily plant-based to increasingly animal-based (Huang & Tian, 2019; Ren et al., 2019). Since animal products, especially red meat and dairy, generate significantly higher carbon emissions and water consumption than plant-based foods, these dietary shifts may exacerbate environmental pressures (Zamani et al., 2018; Salahuddin et al., 2016). However, few studies have examined, from a consumer behavior perspective, how food consumption can be made more environmentally sustainable (Zhang et al., 2019a; Zamani et al., 2018). As noted above, the Internet has become a primary channel for accessing dietary information (Min et al., 2021; Shen et al., 2023). It can raise awareness of the environmental impacts of specific foods and promote environmentally friendly choices (Salahuddin et al., 2016; Zamani et al., 2018). Unlike traditional media such as television, newspapers, and radio, the Internet provides vast, low-cost information without the limitations imposed by specific publishers (Min et al., 2021; Shen et al., 2023). Furthermore, Internet use can improve market efficiency and influence food prices by reducing search and transaction costs (Zamani et al., 2018; Salahuddin et al., 2016). Consequently, the promotion and sale of whole-grain and low-carbon-labeled foods mainly occur online (Salahuddin et al., 2016). Building on this, the present study will further analyze the impact of Internet use on the environmental footprint of food consumption, addressing a gap in the existing literature (Zhang et al., 2019a; Zamani et al., 2018).

A healthy agri-food system should account for both sustainable food consumption and the sustainable development of agriculture. FFCS projects aim to mitigate global warming and enhance environmental and ecological benefits by expanding forest areas to absorb carbon dioxide and implementing a carbon emission trading system to incentivize enterprises to reduce their carbon emissions. On the one hand, FFCS projects contribute to improving air quality (Baumgardner et al., 2012; Smith et al., 2013), promoting off-farm employment of agricultural labor and increasing farmers' income (Aggarwal & Brockington, 2020; Boyd et al., 2007), which is conducive to agricultural TFP growth (Diao et al., 2018; Sheng et al., 2020). However, China has about 18% of the world's population but only 5.51% of the world's forest area, 3.34% of the world's forest stock, and 22.96% of the forest cover (Zhang et al., 2022). The development of FFCS has also raised concerns about China's food security and agricultural development. First of all, due to the lack of incentives and supervision in implementing FFCS projects, some high-quality flat farmland may also be used for carbon sequestration, leading to a decrease in food production (Hu et al., 2021), which will harm sustainable agricultural development. Moreover, the FFCS projects prohibit the cultivation of cash crops such as mushrooms and herbs in the forest, which may affect yields (Rao et al., 2019). Although the existing literature has extensively discussed the impact of FFCS on the allocation of agricultural factors, such as land, labor, employment structure, and income structure, there is limited knowledge about whether FFCS projects can influence agricultural development. Therefore, we will further explore the potential impact of the FFCS project on agricultural sustainable development by using agricultural TFP as a comprehensive index to measure it.

1.3 Research objectives and questions

The primary aims of this thesis are to examine the driving factors shaping a healthy agri-food system in rural China and to assess their impacts on human health and the environment. Building on the aforementioned developments and challenges, this study investigates how changes in the agri-food system influence nutritional health and the environment in rural China from three distinct perspectives: economic, digital, and environmental policy. The specific research questions are as follows:

Research question 1: Can income inequality exacerbate nutritional health risks?

To promote healthy food consumption in rural areas and improve residents' nutritional health, this topic will examine the impact of income inequality on nutritional outcomes. Specifically, using nationally representative data from the China Health and Nutrition Survey (CHNS), three household-level income inequality indices are constructed. The effects of income inequality on body mass index (BMI), underweight, overweight, and obesity are then analyzed using a two-stage least squares (2SLS) approach and a multinomial logistic model. The findings aim to shed light on how reducing income inequality may improve nutritional health and, in turn, contribute to promoting healthier food consumption patterns in rural China.

Research question 2: Can Internet use improve dietary quality and nutritional health?

The rapid development of the Internet has profoundly reshaped people's lifestyles. Beyond serving as the primary platform for acquiring food- and nutrition-related information, it is increasingly being used for food purchases. To assess the overall impact of Internet use on food consumption and nutritional health, this study employs CHNS panel data from 2004 to 2015. First, we examine how Internet use influences dietary quality. Second, given the potential trade-off between Internet use and time spent on physical activity, we investigate its effect on physical exercise. Finally, we analyze the relationship between Internet use and health outcomes, including self-rated health, overweight, obesity, and chronic diseases.

Research question 3: Can Internet use help to achieve sustainable food consumption?

Sustainable food consumption should improve human health while minimizing environmental impacts. To examine the potential role of the Internet in this process, we first estimated environmental footprint factors for different foods from existing literature. Then we calculated household-level food environmental footprints using CHNS data. Employing a two-stage least squares approach, we estimated the effect of Internet use on these footprints. Since animal-derived foods typically impose greater environmental burdens, we further analyzed how Internet use influences the consumption of animal-based environmental footprint factors across different foods using existing literature, and then calculated household-level food environmental footprints using CHNS data. Employing a two-stage least squares approach, we estimated the effect of Internet use on these footprints. Since animal-derived foods typically impose greater environmental burdens, we further analyzed how Internet use influences the consumption of animal-based versus plant-based foods, thereby reshaping individual-level food environmental footprints.

Research question 4: Can the FFCS project benefit agricultural sustainable development?

Environmental policies can mitigate the environmental impact of food consumption, but they may also alter local agricultural factor inputs, such as land, fertilizers, and labor. Therefore, achieving a healthy agro-food system requires that environmental policies generate environmental health benefits without compromising the sustainable development of agriculture. To examine the effect of the FFCS project on agricultural sustainable development, we first used total factor productivity (TFP) as a comprehensive indicator of agricultural sustainable development. We developed a theoretical framework for analyzing the impact of the FFCS project on agriculture. Next, we employed the PSM-DID method to address potential endogeneity arising from sample selection bias and to estimate the causal effect. Additionally, we explored the channels through which the FFCS project affects agricultural TFP. The results show that FFCS projects have increased agricultural TFP by 1.7% to 2.4%. Health, savings, and industrial structure are key channels through which the FFCS project impacts agricultural TFP. Our findings suggest that implementing FFCS projects can simultaneously achieve environmental objectives and enhance agricultural TFP, creating a win-win situation.

1.4 Structure of the dissertation

The remainder of the dissertation is organized as follows. Chapter 2 analyzes the economic impact of income inequality on nutritional health. Chapter 3 examines the role of Internet use in shaping healthy food consumption and nutritional health from a technological perspective. Recognizing that healthy food consumption should also account for environmental sustainability, Chapter 4 explores the impact of Internet use on the environmental footprint of food consumption from an environmental health perspective. Chapter 5 evaluates the FFCS project on agricultural sustainable development. Chapter 6 provides a summary of the main findings, highlights the key contributions, presents policy suggestions and limitations, and discusses the outlook and future research directions. The structure of this dissertation is shown in Figure 1.2.

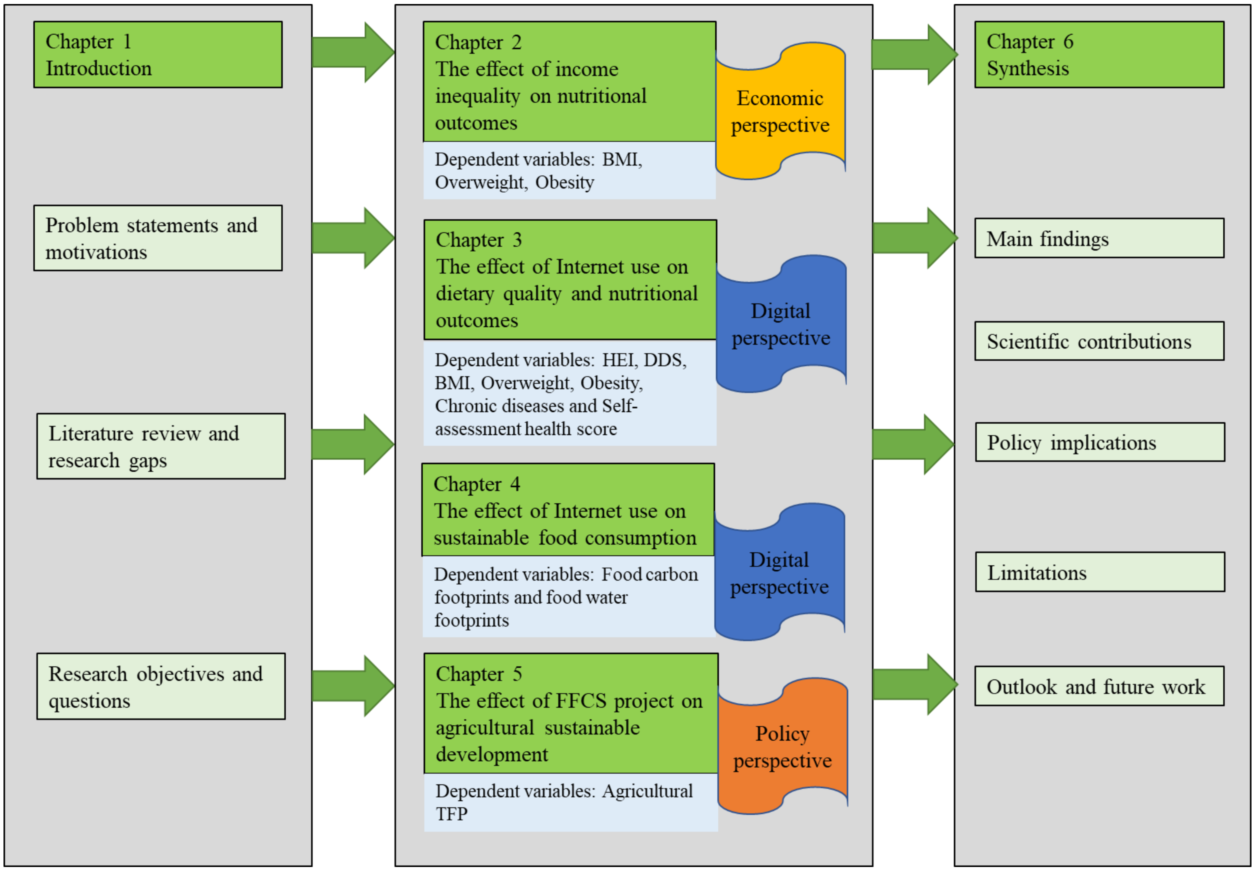

Figure 1.2: Structure of the dissertation. Source: Own operations

Chapter 2 The Effect of Income Inequality on Nutritional Outcomes[2]

2.1 Introduction

Income has been well-documented as one of the most important determinants of nutrition-related health, which is particularly true in a transitional economy like China; yet, less attention has been paid to the role of income inequality. China has recorded impressive growth over the past decades, and since the introduction of its market economy, people's living standards and dietary quality have increased dramatically. However, there is a growing concern about income inequality (Asiseh & Yao, 2016; Li, 2006). According to the estimation from the World Bank and the National Bureau of Statistics of China, China's Gini coefficient increased rapidly from 0.28 in 1981 to 0.49 in 2008, and reached 0.47 in 2017 (Yao & Asiseh, 2019; China Yearbook of Household Survey, 2018). As a result of China's policy of prioritizing efficiency and urban development, a small group of people became rich quickly. However, low-income groups benefited little, especially in rural areas (Cai et al., 2021). The rich are becoming richer and the poor are becoming poorer, which may reduce socioeconomic mobility, undermine the flexible class structure in the countryside, and negatively affect Chinese farmers. The Chinese government has been aware of the potential harm that income inequality can cause in rural China. It has implemented some policies to reduce it, such as China's poverty alleviation policies, which will enable the entire Chinese population to be lifted out of absolute poverty by 2021. However, the issue of income inequality will remain an important challenge for China's rural development for the foreseeable future. Therefore, studying income

[2] This chapter was published as the following open-access article: Liu J, Yanjun R, Glauben T (2021). The effect of income inequality on nutritional outcomes: Evidence from rural China. *Journal of new economy*. **https://jne.usue.ru/en/issues-2021/1053**

inequality in China is necessary for both Chinese farm households and policymakers looking to improve the welfare of rural residents.

Significant structural changes have been observed in household income and dietary patterns in China, and a comprehensive understanding of the effect of income inequality on nutritional outcomes is required. China's per capita national income (GNI) skyrocketed from $1,209.463 in 1995 to $8,222.956 in 2019, closing in on the average of $8,349.300 for upper-middle-income countries, and it is still showing a rapidly rising trend (World Bank Database, 2021). Against this background, the strong effect of budget constraints on the food consumption of Chinese farmers will be muted by the substantial increases in their incomes. Thus, the effect of income inequality on Chinese farmers' nutritional outcomes differs from that of both developed and some developing countries. At the same time, the diets of Chinese farmers have changed dramatically. For example, Chinese farmers are shifting away from the consumption of traditional Chinese foods featuring grains and vegetables to foods that are high in fat and protein (Ren et al., 2019b). Sweeter and more animal-derived foods are also being favoured by more Chinese people (Jolliffe, 2011). These changes will also alter the effect of income inequality on low- and high-income groups. China is a typical transitional economy, and this study examines the effect of income inequality on the nutritional intake of the rural population in China, which has important implications not only for farmers and policymakers in China but also for those in other transition economies.

In this study, we present how income inequality affects farmers' nutritional health in terms of both the absolute income hypothesis and the relative income hypothesis. The absolute income hypothesis suggests that higher income groups tend to have better health and nutritional outcomes. In other words, the absolute income hypothesis suggests that farmers' personal health and income are concave, and that people with higher income may have a lower risk of overweight and obesity.

According to this hypothesis, higher income groups have a greater ability to purchase higher quality food and therefore have better food consumption and nutritional intake choices, and unhealthy and poor nutritional outputs are the result of low or extreme poverty. Within the same group, rising income inequality means that more wealth is taken by fewer people, which is good for the health and nutritional outcomes of the rich but bad for the poor, and the impact on the group as a whole is uncertain.

The relative income hypothesis states that health depends on an individual's income relative to others in his or her group, rather than an individual's absolute income, and that an individual's relative rank in the group is correlated with health and nutritional outcomes. This hypothesis suggests that relative income is more representative of an individual's ability to obtain goods and services in the same community, and that these things are often correlated with an individual's health and nutritional outcomes. Besides, several psychological and psychiatric factors can have a significant impact on an individual's health and nutritional outcomes. For example, relative poverty compared to people in the same community can cause people to feel stressed and depressed, which can affect the individual's state of health. According to the relative income hypothesis, an increase in income inequality within the same group will result in fewer people with higher incomes and more people with lower incomes, which will be detrimental to the nutrition and health status of individuals. Moreover, this hypothesis also suggests that the harm caused by income inequality occurs mainly among low-income groups.

Based on the absolute and relative income hypotheses, many articles have discussed the effects of income inequality on nutrition and health. However, most existing studies on the effect of income inequality on health and nutrition are based exclusively on samples from developed countries, with mixed findings that may not be applicable to transition economies like China (Du et al., 2004; Ren et al., 2021). Using individual-level data from the 1996–1998 Behavioural Risk Factor Surveillance System, Chang and Christakis (2005) do not find a positive association between income inequality and weight outcomes, such as BMI and the odds of being obese. Nikolaou and Nikolaou (2008) argue that in European Union countries, income inequality mainly affects women, especially middle-aged women, rather than men. However, Pickett and Wilkinson (2015) analysed income inequality and child welfare in 23 wealthy countries. Their findings show that income inequality hurts many aspects of child welfare, such as teenage homicides, infant mortality rates, low birth weights, educational performance, high school dropouts, overweight, and mental health problems (Pickett & Wilkinson, 2015). Bjornstrom (2011) and Matthew and Brodersen (2018) also support the idea that income inequality increases the risk of obesity in American adults. Considering that systematic differences exist between developed and developing countries in terms of the level of medical care, consumers' dietary knowledge, income distribution systems, and food culture (Min et al., 2021), there are also differences in the effect of income inequality on nutritional outcomes. For instance, individuals living in developed countries have higher absolute income levels, so for most farms, budget constraints will not be a significant factor affecting their access to food and nutrition (Ren et al., 2019a). However, for the low-income group, budget constraints may significantly affect the food consumption and nutritional intake of many farmers, so income and income inequality may have different effects across different economies.

While a considerable number of studies have investigated the consequences of income inequality in China, little is known about its effect on nutritional outcomes, especially in rural areas of the country. Several papers have used the Gini coefficient as a proxy variable for income inequality to examine the effect of income inequality on Chinese farmers' health statuses, such as individual mental health scores (Chen & Meltzer, 2008), personal health self-assessments (Li & Zhu, 2006), and chronic diseases, such as hypertension and diabetes (Chen & Meltzer, 2008). Other studies have discussed the channels through which relative poverty indices affect individuals' mental health statuses, and they include social relationships, general trust, and self-confidence (Bakkeli, 2016). However, these studies have mainly focused on the effect of income inequality on health status and neglected the effect it has on nutritional outcomes. Moreover, most of the existing literature uses aggregate indices to represent income inequality, such as the Gini coefficient at the county or community level, which ignores the heterogeneity of the effects of income inequality on individual nutritional outcomes.

Using the absolute income hypothesis, relative income hypothesis, and agricultural economics as theoretical propositions, the purpose of this study includes the following three points. The first purpose of this study is to understand the current state of income inequality in rural China and the relationship between income inequality and nutritional outcomes in a transition country like China. Unlike the existing literature centred on developed economies, this study focuses on the effect of income inequality on nutritional outcomes in a transition economy such as China, which contributes to enriching the literature by examining the topic of income inequality and nutritional outcomes. The second purpose of this study is to test whether the hypothesis that income inequality has a greater impact on low-income groups is appropriate for Chinese farmers. This question needs to take into account the individual heterogeneity of farm households; therefore, we use the individual relative deprivation index instead of the aggregate index to express income inequality, thereby overcoming the limitation of the aggregate index about ignoring individual heterogeneity. The third purpose of this study is to bring more attention to the problem of income inequality among Chinese farmers through our research and to make some targeted suggestions for the Chinese government to deal with this problem, thus promoting the nutrition and welfare of Chinese farmers while also providing some experiences for other transition countries to deal with the problem of income inequality.

2.2 Method and data

2.2.1 Method

In order to explore the relationship between nutritional outcomes and income inequality, we started with a linear regression for BMI as the benchmark model. Afterward, a multinomial logistic regression model was applied for four BMI categories: underweight, normal weight, overweight, and obesity. Finally, a probit model was applied to check the robustness of our results further.

The benchmark model. As mentioned above, BMI is one of the most important indicators of individual nutritional outcomes, and it may be influenced by income inequality. At the same time, farmers' and household characteristics are also important factors affecting BMI, so we followed the studies of Li et al. (2006) and Ren et al. (2019a), and the baseline model for this study was established, as shown in Equation 2-1.

$$BMI_k = \alpha_0 + \beta_1 R_k + \beta_2 I_k + \beta_3 H_k + \varepsilon_k \tag{2-1}$$

In Equation 2-1, BMI_k is the BMI of farmer K, and it is calculated by dividing the body mass by the height squared (kg/m²). R_k is the index measuring the income inequality of farmer *K*, including the ranking of individual income in the community, the Yitzhaki index, and the Kakwani index. I_k is the vector indicating farmers' characteristics, including age, the quadratic term of age, gender, marital status, working situation, and physical activity. H_k represents the household control variables, including household size, household per capita income, and the quadratic term of household per capita income. ε_k is the disturbance term and is assumed to be normally distributed.

We are interested in the coefficient of the income inequality variable (β_1). If it is significantly positive, we can conclude that income inequality increases BMI.

The multinomial logistic model. The BMI cannot determine whether an individual's nutritional outcome is healthy or not. To further estimate the effect of income inequality on nutritional outcomes, we further classified individuals' BMIs into four categories: underweight, normal weight, overweight, and obese.[3] In China, overnutrition is an emerging public health issue and is related to overweight and obesity, but it is estimated that approximately 150.8 million people are undernourished, especially in rural areas.[4] The available research on the nutritional effects of income inequality exclusively focuses on the issue of overnutrition, and less attention has been paid to undernutrition (Rathavuth & Rathmony, 2007). We aimed to examine whether income inequality has an effect on the risk of being underweight, overweight, or obese, using normal weight as the reference group. Since our dependent variables are multi-categorical, the ordinary least squares (OLS) method was not appropriate. Therefore, we used a multinomial logistic model to analyse the effect of income inequality on underweight, overweight, and obesity. The model is defined as follows:

$$\begin{cases} \ln(P_1/P_2) = \alpha_1 + \beta_{11}R_k + \beta_{12}I_k + \beta_{13}H_k + \varepsilon_k \\ \ln(P_3/P_2) = \alpha_2 + \beta_{21}R_k + \beta_{22}I_k + \beta_{23}H_k + \varepsilon_k \\ \ln(P_4/P_2) = \alpha_3 + \beta_{31}R_k + \beta_{32}I_k + \beta_{33}H_k + \varepsilon_k \end{cases} \tag{2-2}$$

In Equation 2-2, P_1, P_2, P_3 and P_4 represent the probability of being underweight, normal weight, overweight and obese, respectively, and the vectors R_k, I_k and H_k are the same as those used in

[3] The detailed classification is given in Section 3.2.
[4] https://www.wfp.org/countries/china (accessed on 17 August 2020).

model (1). In this case, the maximum likelihood method is used to estimate the parameters to be calculated using Equation 2-2.

We are interested in the coefficients of the income inequality variable ($\beta_{11}, \beta_{21}, \beta_{31}$). If they are significantly positive, we can conclude that income inequality may worsen nutritional outcomes by increasing the risk of being underweight, overweight, or obese. The lower the income, the greater the individual deprivation index (Li & Zhu, 2006), and this will result in the lower income group suffering from a higher risk of being underweight, overweight, or obese.

The probit model. To further check the robustness of our estimation results, we also defined the nutritional outcomes as a binary outcome: being overweight/obese or otherwise. This is a common strategy in empirical studies (Morris, 2007). The probit model is applied as follows:

$$Probit(Y_k = 1) = \beta_1 R_k + \beta_2 I_k + \beta_3 H_k + \varepsilon_k \tag{2-3}$$

In Equation 2-3, the dependent variable Y_k is a binary variable; it equals 1 if the *K*th individual is overweight or obesity and 0 otherwise. The vectors R_k, I_k and H_k are the same variables as those used in models (1) and (2). The random error term ε_k is assumed to follow a normal distribution. We used the maximum likelihood estimation method to estimate the relevant parameters. If the sign of the coefficient of income inequality in the three models is the same, all positive or all negative, and there is little difference in the significance level, then our result is robust; otherwise, it is not robust.

2.2.2 Data

The sample. We used data from the CHNS. The CHNS was designed to study health and nutrition-related issues in China and was conducted under an international collaborative project between the National Institute of Nutrition and Food Safety of the Chinese Centre for Disease Control and

Prevention and the Carolina Population Centre at the University of North Carolina in Chapel Hill. The CHNS was first carried out in 1989. Since then, another nine waves have been conducted in 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011 and 2015 in nine provinces, namely Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning and Shandong (since 2011, three additional municipal cities have been included: Beijing, Chongqing and Shanghai), which vary substantially in terms of their geography, economic development and public resources, as well as about health indicators. The CHNS data include detailed information about the characteristics of the households and individuals surveyed, as well as health-related information, such as that concerning physical conditions, healthy behaviours, and nutritional intake. We used the most recent data from 2015 for our analysis.

CHNS2015 covers 12 provinces of China (Heilongjiang, Liaoning, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou, Shaanxi, Yunnan, and Zhejiang) and three autonomous cities (Beijing, Shanghai, and Chongqing), with a total of 360 communities and 20,914 people. Our sample is limited to all adults aged 18 to 70 at the time of the survey. It provides a complete set of data on individual demographics and household characteristics (age, gender, education, marital status, employment status, physical activities, household size, and household income). Since we needed to construct an index of income inequality, non-positive reports of household income were eliminated. Consequently, our final sample consisted of 6,379 observations.

Dependent variables. As aforementioned, our main dependent variables are nutritional outcomes, which are measured using BMI and the four binary variables of being underweight, normal weight, overweight, or obese. BMI is calculated by dividing the body mass by the height squared (kg/m^2). According to the criteria proposed by the World Health Organisation (WHO, 2000), a BMI below 18.5 is defined as underweight, a BMI equal to 25 or more is considered overweight, and a BMI greater than or equal to 30 means that the individual is obese. However, Wu (2006) believes that this classification from the WHO is commonly used for Western people but that it does not apply to China. Therefore, we follow Zhou (2002) and Ren (2019a) in defining people with BMIs less than 18 as underweight, BMIs greater than or equal to 24 as overweight, and BMIs greater than 28 as obese (Zhou, 2002).

The summary statistics of the primary dependent variables are presented in Table 2.1. It shows that the average BMI is more than 24 for the pooled sample, which is higher than studies using the previous waves of the CHNS data (Ren et al., 2019a). Nearly half of the participants considered in our sample are overweight, and 15.3% of them are obese. According to the National Bureau of Statistics of China, China had a total population of nearly 603.45 million in 2015, and the overweight and obese populations calculated using this method were nearly 295.690 million and 33.535 million, respectively. Nevertheless, 2.8% of individuals are observed to be underweight in our sample. Additionally, we also find a significant difference in the BMIs between the male and female samples; males tend to have a BMI that is 0.276 higher than that of females. No significant differences are found for overweight and obesity, while it is revealed that females are more likely to be underweight.

Independent variables. Income inequality is the primary independent variable of interest in this study. Generally, income inequality is used to show how unevenly income is distributed throughout a given population. The less equal the distribution, the higher the income inequality is. There are plenty of methods for measuring income inequality (Li & Zhu, 2006). Following previous studies, we selected three widely used methods to measure the income inequality in our sample: the ranking of individual incomes in the community, the Yitzhaki index, and the Kakwani index.

Table 2.1: Variable definitions and descriptive statistics

Variable	Definition	All	Females	Males	Difference
Dependent variables					
BMI	Weight/height^2	24.368	24.236	24.512	-0.276***
Underweight	1 if the individual is underweight, 0 otherwise	0.028	0.032	0.024	0.007*
Normal weight	1 if the individual is normal weight, 0 otherwise	0.481	0.488	0.475	0.013
Overweight	1 if the individual is overweight, 0 otherwise	0.490	0.480	0.501	-0.020
Obesity	1 if the individual is obese, 0 otherwise	0.155	0.153	0.157	-0.004
Independent variables					
Rank	Gentile rank (incomes in descending order) in the community	20.918	21.225	20.583	0.642**
Yitzhaki index	Yitzhaki = $\sum(y_i - y_j)/N$, for all $y_i > y_j$ where y_i is the income of person *I* and N is the size of the community	12.605	12.994	12.180	0.814***
Kakwani index	Yitzhaki/μ_k, μ_k is the mean of Yitzhaki in the community	1.000	1.026	0.971	0.055***
Control variables					
Age	Age in years	47.740	47.862	47.607	0.254
Age squared	Age squared	2456.066	2464.716	2450.014	14.702
Gender	Male = 1; Female = 0	0.478	0.00	1.00	-1.00
Education	Years of education	9.896	9.143	10.718	-1.575***
Marital status	1 if the individual is married, 0 otherwise	0.875	0.889	0.859	0.029***
Occupation	1 if the individual is currently working, 0 otherwise	0.563	0.460	0.676	-0.217***
Physical activities	1 if the individual's work requires heavy physical activities,[5] 0 otherwise	0.182	0.134	0.235	-0.101***
Income	Per capita household income adjusted to 2015 price index (1000 CNY)	29.128	28.007	30.309	-2.303**
Household size	The total number of household members	4.864	4.911	4.813	0.098*
Observations	The number of observations	6,379	6,379	6,379	6,379

Note: *, **, and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively. Source: Author's estimations using the CHNS data (2015).

[5] Jobs that involve heavy physical activity include being a steel worker, lumber worker, mason, farmer, athlete and dancer.

In this study, since the database only includes total household income and the number of household members, we use the per capita household income to represent individual income. Specifically, samples from the same community are ranked in descending order by household income per capita (household income is adjusted according to Organisation for Economic Cooperation and Development (OECD) criteria). That is, the sample with rank = 1 has the highest per capita household income at the community level. A higher ranking indicates higher income inequality for a household within the community. Second, the Yitzhaki index was introduced by Yitzhaki in 1979 and has been used by many researchers to study income inequality (Li & Zhu, 2006). The Yitzhaki index provides a more accurate picture of income differences among individual community members than ranking. The specific formula for the Yitzhaki index is shown in Equation 2-4.

$$Yitzhaki_k = \frac{1}{n}\sum_{i=1}^{k-1}(income_i - income_k) \tag{2-4}$$

In Equation 2-4, $Yitzhaki_k$ is the Yitzhaki index of the *Kth* individual, and $income_k$ is the annual per capita household income of the *Kth* farm household. $income_i$ denotes the per capita income of households in the same community as farmer k and whose annual household income is greater than K, and n is the total number of people in the community. Note that since we calculate the Yitzhaki index using the per capita household income, it is the same for all the persons in the same household.

The third measurement is the Kakwani index, which was developed from the Yitzhaki index by Kakwani (Li & Zhu, 2006). In fact, the Kakwani index is the ratio of the individual Yitzhaki index divided by the average of the Yitzhaki index of all the people in the community μ_K. In contrast to the Yitzhaki index, the Kakwani index is no longer sensitive to population size. The specific formula for the Kakwani index is shown in Equation 2-5.

$$Kakwani_k = \frac{1}{n\mu_K}\sum_{i=1}^{k-1}(income_i - income_k) \tag{2-5}$$

In Equation 2-5, $Kakwani_k$ is the Kakwani index of farmer K. i, n, $income_i$ and $income_k$ are the same as in Equation 2-4 and μ_K denotes the average Yitzhaki index of the community members of farmer K. The Kakwani index differs from the Yitzhaki index in that it considers the effect of population size on the income inequality index.

Control variables. The main control variables in this study consisted of two components: individual demographic variables and family characteristics. Individual demographic variables included age, gender, education, marital status, employment status, and physical activity levels. Household characteristics mainly consisted of income and household size. As shown in Table 2.1, the average age of the participants in our sample is 47 years old, and nearly half of them are males; the average length of time spent in education is approximately 9.9 years; and more than 87.5% and 56.3% of them are married and are currently working, respectively. It also shows how 18.2% of our sample perform heavy physical activities. Regarding the household controls, it is observed that the per capita household income is almost 30,000 CNY.[6] The average household size is 4.8 individuals.

2.3. Results and discussion

2.3.1 The effect of income inequality on BMI

The main results regarding the BMI estimations are presented in Table 2.2. Columns 1, 2, and 3 in Table 2.2 represent the results of the effect of three variables, Rank, Yitzhaki index, and Kakwani

[6] 1 CNY ≈ 0.16 USD in 2015.

index, on BMI, respectively. In general, the estimates of the three indices are largely consistent, showing a positive and significant effect of income inequality on BMI. This suggests that increasing income inequality is associated with higher BMIs for rural residents. Specifically, keeping the other variables unchanged, a one-rank increase in an individual's income ranking within the community leads to a 0.1% increase in that person's BMI. The coefficients of both the Yitzhaki and Kakwani indices are also positive, which indicates that an increase in income inequality significantly increases individual BMIs.

It should be noted that the research of Ren et al. (2019a) suggests an inverted U-shaped relationship between the income of rural residents and their BMIs, with the critical point of the quadratic curve of BMI and income positioned at around 26,627 CNY. Before 2011, low-income farmers in China were unlikely to be overweight. However, our findings show that, in rural China in 2015, low-income groups are often likely to have a higher BMI and that there is a significant positive correlation between the individual income inequality index and nutrition outcomes.

Regarding the control variables, the results show a non-linear relationship between age and BMI, which is consistent with our expectation that middle-aged people are more likely to have a higher risk of obesity. The inflection point of age appears around the age of 44; that is, before 44, BMI will increase with age, but after 44, BMI will gradually decrease with any further increase in age. Our results also show that the males' BMI is significantly higher than that of females, which may be the result of Chinese women being more concerned about their weight (Ren et al., 2021). Similar to previous studies (Woo et al.,2007), we also found that individuals' education levels and the intensity of the physical activities they perform are negatively correlated with BMI.

Table 2.2: The effect of income inequality on BMI

Variables	Dependent variable: BMI		
	(1)	(2)	(3)
Rank	0.001*		
	(0.00)		
Yitzhaki index		0.001*	
		(0.00)	
Kakwani index			0.011*
			(0.01)
Age	0.009***	0.009***	0.009***
	(0.00)	(0.00)	(0.00)
Age squared	-0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)
Gender	0.015***	0.015***	0.015***
	(0.00)	(0.00)	(0.00)
Education	-0.001**	-0.001*	-0.001*
	(0.00)	(0.00)	(0.00)
Marital status	-0.005	-0.005	-0.005
	(0.01)	(0.01)	(0.01)
Occupation	0.004	0.004	0.004
	(0.00)	(0.00)	(0.00)
Physical activities	-0.023***	-0.023***	-0.023***
	(0.01)	(0.01)	(0.01)
LnIncome	-0.011	-0.009	-0.009
	(0.01)	(0.01)	(0.01)
LnIncome squared	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)
Household size	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)
Constant	3.031***	3.037***	3.018***
	(0.07)	(0.07)	(0.07)
Province controls	Yes	Yes	Yes
Number of observations	6,379	6,379	6,379

Note: *, **, and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively, and the numbers in brackets are standard errors. The results are cluster-corrected at the community level. Source: Author's estimations using the CHNS data (2015).

2.3.2 The effect of income inequality on underweight, overweight, and obesity

As shown in Table 2.3, the results of the multinomial logistic model are mainly consistent with the results from the OLS regressions. The coefficients of these three indicators of individual income inequality are all significantly positive in the estimation of overweight and obesity, except the coefficient of the Yitzhaki index, which is shown to be positive but insignificant. This result generally suggests that an increase in individual income inequality can significantly increase the risk of being obese and overweight. Unlike overweight and obesity, our results indicate that income inequality among rural residents has no significant effect on underweight. This suggests that an economic reason might not be the determinant of being underweight and that there might be some other reasons, such as cultural ones. Income inequality has a significant effect on overweight and obesity, but not on underweight. This may be the result of the changing food intake of Chinese farmers as their incomes continue to rise. In rural China, the main nutrition-related problem facing Chinese farmers has shifted away from the demand for more food to the demand for higher-quality food. The diversity of food consumption and how to achieve a balanced intake of nutrients are also new problems for most Chinese farmers.

We want to emphasise that, from the perspective of nutritional outcomes, the effect of income inequality on Chinese farmers is likely to be concentrated in relatively low-income groups. That is to say, if the income inequality of Chinese farmers increases further, it will lead to a higher risk of overweight and obesity for people with lower incomes. On the one hand, for rural low-income groups, although they can meet their basic food and nutritional needs, their diet may not be balanced. For example, a high carbohydrate intake may be one factor that increases the risk of obesity among Chinese farmers (Burggraf et al., 2015). On the other hand, low-income farmers tend to face greater social and economic pressure, which will not only directly harm the psychological health of farmers and increase their risk of obesity (Shimokawa, 2013). However, they may also require farmers to invest more energy and time in agricultural production activities, potentially disrupting their regular diet. This puts low-income farmers at a higher risk of being overweight and obese.

Table 2.3: The effect of income inequality on underweight, overweight, and obesity

Variables	Underweight			Overweight			Obesity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rank	0.004			0.004			0.009*		
	(0.01)			(0.00)			(0.01)		
Yitzhaki index		-0.004			0.006*			0.013**	
		(0.01)			(0.00)			(0.01)	
Kakwani index			-0.208			0.059			0.209*
			(0.25)			(0.09)			(0.11)
Age	-0.186***	-0.187***	-0.187***	0.119***	0.120***	0.119***	0.067***	0.069***	0.067***
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age squared	0.002***	0.002***	0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	0.00	0.00	0.00	0.00	0.00	0.00
Gender	-0.27	-0.271	-0.274	0.125*	0.129*	0.125*	0.131	0.139	0.133
	(0.19)	(0.19)	(0.19)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)
Education	0.024	0.025	0.027	-0.009	-0.009	-0.008	-0.009	-0.009	-0.009
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Marital status	0.065	0.066	0.061	0.180*	0.178*	0.179*	-0.033	-0.039	-0.035
	(0.26)	(0.26)	(0.26)	(0.10)	(0.10)	(0.10)	(0.15)	(0.15)	(0.15)
Occupation	-0.025	-0.026	-0.026	0.006	0.007	0.008	-0.02	-0.018	-0.017
	(0.20)	(0.20)	(0.20)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)
Physical activities	0.259	0.254	0.254	-0.087	-0.086	-0.086	-0.224**	-0.222**	-0.220**
	(0.25)	(0.25)	(0.25)	(0.09)	(0.09)	(0.09)	(0.11)	(0.11)	(0.11)
LnIncome	1.12	1.213	1.265	0.015	0.016	0.039	-0.049	-0.044	-0.019
	(0.79)	(0.78)	(0.77)	(0.19)	(0.19)	(0.19)	(0.27)	(0.28)	(0.28)
LnIncome squared	-0.063	-0.071	-0.078*	0.001	0.001	0.000	0.009	0.007	0.008
	(0.05)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Household size	0.065	0.065	0.064	-0.007	-0.005	-0.006	0.026	0.029	0.03
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	-4.782	-4.775	-4.374	-3.224***	-3.197***	-3.269***	-2.491*	0.013**	-2.757*
	(3.66)	(3.70)	(3.66)	(1.00)	(0.97)	(1.00)	(1.41)	(0.01)	(1.46)
Province controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	6,379	6,379	6,379	6,379	6,379	6,379	6,379	6,379	6,379

Note: *, **, and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively, and the numbers in brackets are standard errors. The results are cluster-corrected at the community level. Source: Author's estimations using the CHNS data (2015)

2.3.3 Robustness check

To further check the robustness of our results, a binary outcome was defined and estimated using a probit model. The estimation results of the probit model are shown in Table 2.4. The main results are broadly consistent with those from the OLS and multilogit estimations. Thus, we can conclude that income inequality can significantly increase the unhealthy nutritional outcomes of being overweight and obese.

Table 2.4: The estimates of the robustness test

Variables	**Overweight**			**Obesity**		
	(1)	(2)	(3)	(4)	(5)	(6)
Rank	0.003			0.004*		
	(0.00)			(0.00)		
Yitzhaki index		0.005**			0.006**	
		(0.00)			(0.00)	
Kakwani index			0.070			0.099*
			(0.05)			(0.06)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	6,379	6,379	6,379	6,379	6,379	6,379

Note: *, **, and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively, and the numbers in brackets are standard errors. The results are cluster-corrected at the community level. Source: Author's estimations using the CHNS data (2015).

2.3.4 Heterogeneity analysis

As mentioned above, significant differences exist in nutritional outcomes between males and females in rural China. Thus, it is necessary to examine if there are gender-specific effects of income inequality on nutritional outcomes. In this section, we will discuss the heterogeneous effect of income inequality on the nutritional outcomes for the male and female samples using OLS and multinomial logistic estimations.

As shown in Table 2.5, for the male sample, increasing income inequality significantly increases their BMI, while it has no significant effect on the change in the BMI of the females. The multinomial logistic model regression results also showed that income inequality significantly increases the risk of overweight for males, but has no significant effect on the equivalent for females. In the model of the effect of income inequality on obesity, it is noteworthy that the Y-index is significant for both men and women, suggesting that income inequality may have an effect on obesity in both. However, we also need to note that the coefficient of the female sample (0.001) is much lower than (and, in fact, only 1/16) that of the male sample (0.016). This suggests that the worsening of income inequality in rural China mainly significantly increases the risk of obesity in males, while the effect on obesity in females is minimal.

Table 2.5: The estimations of the heterogeneity analysis

Variables	**BMI**			**Underweight**			**Overweight**			**Obesity**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Male sample												
Rank	0.023**			-0.002			0.008			0.014**		
	(2.55)			(0.01)			(0.00)			(0.01)		
Yitzhaki		0.001**			0.003			0.013**			0.016**	
		(2.72)			(0.01)			(0.00)			(0.01)	
Kakwani			0.022**			-0.118			0.152**			0.352**
			(2.73)			(0.33)			(0.08)			(0.15)
Other	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052
Female												
Rank	0.004			0.009			0.000			0.006		
	(0.01)			(0.01)			(0.00)			(0.01)		
Yitzhaki		-0.000			-0.008			0.001			0.001**	
		(0.00)			(0.01)			(0.00)			(0.01)	
Kakwani			0.001			-0.304			-0.029			0.096
			(0.01)			(0.32)			(0.11)			(0.13)
Other	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327

Note: *, **, and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively, and the numbers in brackets are standard errors. The results are cluster-corrected at the community level. Source: Author's estimations using the CHNS data (2015). Note that: A. BMI is estimated by OLS estimation. B. Underweight, overweight, and obesity are estimated by multinomial logistic estimation.

2.4 Conclusion

Since the reform and opening up of the country, the per capita income of Chinese farmers has increased rapidly, and their living environments and nutritional intake have changed significantly. These changes have switched the nutritional problem faced by Chinese farmers from a calorie deficit to an excess of calories. Based on the latest data from the CHNS in 2015, we explored the effect of income inequality on nutritional outcomes, including BMI, underweight, overweight, and obesity statuses. A set of measurements for income inequality is considered. Some studies have shown that high-income groups in China have a higher risk of obesity, but our results show that low-income groups have a higher risk of obesity. Moreover, the current increase in income inequality in rural China may further increase the risk of overweight and obesity among farmers with relatively low incomes. The findings are consistent when various model specifications are applied.

There are two ways to understand why increasing income inequality in China today primarily increases the risk of obesity in low-income groups. The first possible reason is that income inequality may have a positive effect on BMI by compromising individual food and nutritional intake. For instance, unlike in China in the 1980s, when the country had just implemented the reform and opening-up policy, most Chinese people are no longer suffering from hunger (Yuan et al., 2019). Therefore, food diversity and whether it is of high quality may have a greater effect on nutritional outcomes than larger quantities of food (Ren et al., 2019). It is argued that low-income groups tend to have unhealthy food consumption habits, and their food consumption is usually less diverse due to budget constraints that negatively affect their nutritional intake (Li & Lopez, 2016; Yuan, 2017). However, after a certain income level, further increases in income have little effect on individual nutritional intake. This means that further increases in the income of high-income farmers may not have a positive effect on their nutritional outcomes. Therefore, income inequality may positively affect nutritional outcomes by undermining food diversity and dietary preferences, mainly among low-income groups.

The second possible reason is that income inequality may also negatively affect BMI in low-income groups by undermining their social relationships, general trust, and self-confidence. In general, people in areas with higher levels of income inequality tend to be more likely to agree that most people cannot be trusted, and they have poorer social relationships and more negative psychological states (Sekabira & Qaim, 2017). In addition, these negative psychological factors may contribute to irregular eating habits and are detrimental to the spread and dissemination of nutritional knowledge. Given that most people in China no longer suffer from hunger, the relative income of households has a greater effect on individual nutritional outcomes than absolute income at the community level from an individual psychological perspective. The adverse effect of income inequality on nutrition and health in China is more pronounced in low-income groups, as they typically face more strained social relationships and low self-confidence.

Interestingly, the heterogeneity results of this study suggest that income inequality primarily affects nutritional outcomes in males. Since the vast majority of income in rural Chinese households comes from male members, and women are usually more concerned with their weight, income inequality likely has no effect on women's risk of being overweight. The reason for the heterogeneity between male and female samples may come from two sources. On the one hand, in rural China, the primary income of most families comes from men, and men often face more economic pressure than women. Therefore, the effect of income inequality on men may be greater than that on women. Besides, a more important reason may be that Chinese women with both high and low incomes pay much attention to their weight, and they often try to control it in various ways, such as through dieting, exercising, or even taking diet pills. These artificial interventions counteract the effect of income inequality on the risk of obesity, and thus, income inequality will increase the risk of obesity mainly in the male population.

In the context of the adverse effect of income inequality on farmers' nutritional outcomes in China, the findings of this study have several important policy implications. First, we suggest that the Chinese government should pay more attention to income inequality while working to improve the incomes of Chinese farmers. Second, since China has limited policies to improve nutrition in rural areas, the government should draw lessons from the experiences of developed countries and implement targeted nutrition programs in these areas to enhance the nutritional status of Chinese farmers. Third, men and low-income groups in rural areas of China may face more serious nutritional problems; therefore, China's rural nutrition policies should give more consideration to men and low-income groups.

Overall, this study also has some shortcomings. First, although our research sample is representative, it only contains survey data from 2015, so it would be better if researchers could use panel data from more recent years. Another limitation of this study is that we only focus on one dimension of income inequality, namely inequality at the community level. Further research could focus on income inequality in communities as well as at the township and county levels.

Chapter 3 The Effect of Internet Use on Dietary Quality and Nutritional Outcomes[7]

3.1 Introduction

In the past four decades, the Chinese dietary pattern has undergone significant changes, mainly characterized by higher intakes of fats, added caloric sweeteners, animal source foods, and a higher reliance on processed foods. These changes have important consequences. First, increasing food consumption could improve the nutritional status of Chinese residents. According to estimates from the Food and Agriculture Organization of the United Nations (FAO), the prevalence of malnutrition in China has dropped from 24% in the 1990s to less than 10% (Huang & Tian,2019). However, the overconsumption of high-calorie foods and processed foods is associated with increased rates of non-communicable diseases such as overweight, obesity, and diabetes. It is reported that more than half of Chinese residents are overweight or obese, with the overweight and obese rates being 34.3% and 16.4% respectively (Pan et al.,2021). Compared to urban areas in China, rural areas have lower incomes, poor infrastructure, and often limited access to food and markets. As a result, overweight and obesity have become a significant public health problem, but about 150.8 million people in China are still malnourished or micronutrient-deficient (Yuan et al.,2018; Ren et al.,2021). Thus, it is important to understand the drivers of diet transition and nutrition outcomes.

Existing studies have mainly discussed the effects of income and urbanization on nutrient intake and health outcomes, while little attention has been paid to the role of Internet use. The literature

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finds that the income elasticity of animal products (such as milk and its products, meat, and aquatic products) is high. In contrast, that of staple foods such as whole grains and starches is small or even negative (Huang & Tian,2019). As a result, the diets of low-income people tend to be dominated by staple foods, which are the most cost-effective source of calories. As incomes rise, consumers increasingly focus on other attributes of food in addition to nutrition, such as appearance, taste, status value, odor, and degree of processing (Tian & Yu,2015). Healthy foods generally cost more, and low-income people are more likely to settle for poor health choices in developed countries (Ren et al.,2019). Study also found that income affects health through five channels: nutritional intake, dietary diversity, dietary knowledge, food preferences, and eating out (Ren et al., 2021; Ren et al., 2019). Urbanization may also affect nutritional transition and health. This is because people in cities are often closer to markets and have a wider choice of food (Ren et al.,2021). In addition, in the process of urbanization, individuals with different food cultural backgrounds influence each other (Smart et al.,2020). This interaction may lead to a shift in food preferences, so the nutritional transition also changes with the development of cities.

Internet use may also affect nutritional intake and health outcomes, but results are mixed, and there is a lack of research on rural areas in developing countries. First, Internet use can improve food accessibility by allowing residents to access food that is not available in nearby supermarkets (Shen et al.,2023). Second, the Internet can reduce the transaction costs in the agricultural market and promote farmers' market participation, thereby improving consumers' affordability of food. More importantly, the Internet is the primary channel for accessing food and nutrition information, and Internet use can further improve consumer dietary knowledge (Min et al.,2021). These changes can further improve the dietary quality of rural residents. Based on the household survey data of 10,042 rural households in six provinces in China, Xue et al. (2021) found that Internet use can increase calorie, protein, and fat intake, thereby improving the nutritional status of rural residents. Shen et al. found that the dietary diversity of Internet users is higher than that of respondents who do not use the Internet (Shen et al.,2023). The results of Ma and Jin's (2022) study showed that Internet use can significantly improve the dietary quality of rural residents in China. Moreover, one possible channel is that Internet use improves rural residents' dietary knowledge, thereby optimizing their dietary structure. Cui et al. (2023) found that Internet use increases dietary quality by cultivating consumers' more positive attitudes towards diet. Similar results have been confirmed in other countries, such as Kenya and Australia (Muange & Ngigi, 2021; Pollard et al., 2015). These studies confirm that Internet use improves dietary quality in rural areas of China. Higher dietary quality means better nutritional health (Aghasi et al., 2020; Park & Kwon, 2018). In addition, the Internet can also serve as a way to promote healthy eating habits and increase physical activity interventions to reduce the risk of chronic diseases such as obesity and high blood pressure (Banos et al.,2015).

However, Internet use also hurts nutrition and health. Other studies have suggested that Internet use may increase the risk of overweight and obesity by increasing sedentary lifestyles and decreasing the amount of time spent outside (Wang et al.,2012). Internet addiction, especially among adolescents, can significantly affect eating behavior and nutritional health. Specifically, Internet-addictive users had higher rates of irregular bedtimes, smoking, and alcohol abuse than non-addictive Internet users. In addition, among high-risk Internet users, irregular dietary behaviors due to loss of appetite, frequent skipping meals, and snacking may lead to unbalanced nutrient intake and health problems (Ayran et al.,2021). Physical activity is considered to be an important way to maintain caloric balance and health. However, excessive use of the Internet may reduce the time spent on physical activity. According to the 51st China Internet Development

Statistics Report, Chinese netizens spend an average of 3.8 hours online every day. It should be noted that the majority of time spent online in rural China is spent watching videos and playing video games (Ma et al.,2020). Therefore, there may be a substitution effect between Internet use and physical activities. In other words, Internet use may reduce the physical activity of rural residents and therefore have adverse effects on nutrition and health.

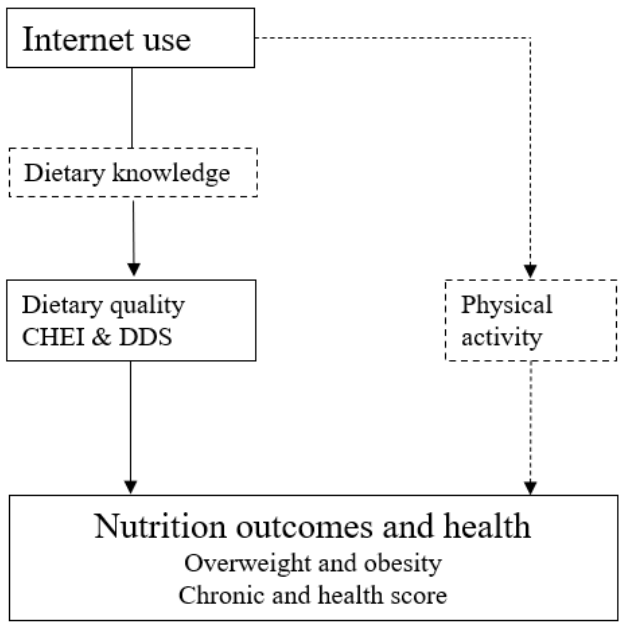

Figure 3.1: Theoretical analysis framework

The theoretical framework of how Internet use affects nutritional intake and health outcomes is shown in Figure 3.1. In the past few decades, China's Internet penetration has been on an upward trend, and by the end of 2016, the number of Internet users in China reached 731 million, ranking first in the world (Ma & Jin, 2022). According to the China Internet Network Information Center (CNNIC), there will be nearly 1.051 billion Internet users in China by 2022, and the Internet penetration rate will reach 74.4%. Figure 3.2 shows the trend of Internet development in China and the world. As shown in Figure 3.2, China leads the world in Internet users, but compared with many European and American companies, there is still great room for development. Therefore, the effects of Internet use on nutritional intake and health outcomes may be long-lasting, and it is important to understand how Internet use affects nutritional intake and health outcomes in rural China.

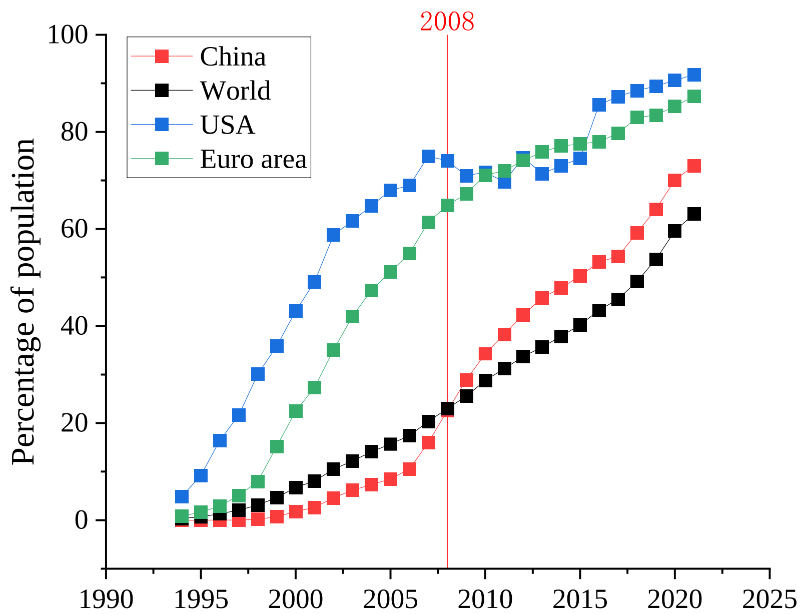

Figure 3.2: Internet use in China and the world from 1994 to 2021

Data source: The World Bank. https://data.worldbank.org/

The objective of the study is to understand better the effect of Internet use on nutritional intakes and health outcomes, and to shed light on its underlying channels. To this end, using CHNS panel data from 2004 to 2015, we employ regression models to quantify the effects and use instrumental variables methods to solve the potential endogeneity problem.

This study contributes to the existing literature in the following three ways. First, unlike previous studies that focus on the influence of urban residents' Internet use on nutritional health, this study expands the content of existing studies in rural areas. Second, extant literature only focuses on the causal relationship between Internet use and nutritional health, without exploring the influencing mechanism. Therefore, the second contribution of this study is to provide a more detailed discussion of how Internet use may influence nutritional intake and health outcomes through two potential channels: diet quality and physical activity. Third, studies have been extensively done in the developed world, while Internet use and nutritional health in most developing nations have received little attention. The results of this study not only have important reference value for the sustainable development of rural areas in China, but also have important reference value for the formulation of food policies and digital economy development systems in developing countries such as India, Vietnam, and Thailand.

3.2 Method and Data

3.2.1 Method

To examine the effect of Internet use on food consumption and health in rural China, this study used the following benchmark model:

$$Y_{it} = \alpha_0 + \alpha_1 Internet_{it} + \alpha_2 X_{it} + \varepsilon_{it} \tag{3-1}$$

where Y_{it} is the dependent variables such as HEI, DDS, and health score; $Internet$ is the independent variable and α_1 is the average treatment effect of Internet use on food consumption and health; X_{it} is a series of control variable like age, marital status, education, work status, household income, and family size; and the ε_{it} is the error term.

In this study, three key dependent variables of overweight, obesity, and chronic disease are binary. To investigate the relationship between Internet use and these dummy variables, we start with the benchmark model as Equation 3-1.

$$\Pr(Z_{it} = 1 \mid Internet_{it}, X) = \theta_0 + \theta_1 Internet_{it} + \theta_2 X_{it} + \varepsilon_{it} \tag{3-2}$$

where the dependent variable Z_{it} includes overweight, obesity, and chronic disease; θ_1 is the change in the probability of using the Internet; Other variables are the same as in Equation 3-2.

When the endogeneity problem is not considered, the estimated coefficients of α_1 and θ_1 are unbiased and consistent; however, the respondents can self-select whether to use the Internet or not. In other words, the sample is not random. Besides, some unobserved variables that have changed over the years could also affect food consumption and health. These problems may lead to bias and inconsistencies in estimated results.

To solve these problems, we applied the instrumental variable estimation to calculate the "net" effect of Internet use on food consumption and health, as shown in Equations 3-3 and 3-4. Similarly, the instrumental variable estimation for overweight, obesity, and chronic disease is shown in Equations 3-3 and 3-5.

$$Internet_{it} = \beta_0 + \beta_1 IV_{it} + \beta_2 X_{it} + \tau_{it} \tag{3-3}$$

$$Y_{it} = \gamma_0 + \gamma_1 \widehat{Internet}_{it} + \gamma_2 X_{it} + \varphi_{it} \tag{3-4}$$

$$\Pr(Z_{it} = 1 \mid Internet_{it}, X) = \tau_0 + \tau_1 \widehat{Internet}_{it} + \tau_2 X_{it} + \sigma_{it} \tag{3-5}$$

where IV_{it} is the instrumental variable of Internet use; X_{it} is several control variables; $\widehat{Internet}_{it}$ is the predicted value of $Internet_{it}$; γ_1 is the net effect of Internet use on food consumption and health; τ_1 is the change in the probability of using Internet; Here, γ_1 and τ_1 are unbiased and consistent.

In this study, we take the proportion of residents using the Internet to the total village residents as the instrumental variable. This instrumental variable is expected to be valid mainly for two reasons. First, it has a direct effect on Internet use. Because the residents live close to each other in rural

China, there is a replication effect for Internet use among neighbors (Sun et al.,2023). Second, it is exogenous to food consumption and health at the individual level, as it can influence these factors only by affecting their Internet use. Note that this instrumental variable has been widely used in previous studies (Ma & Abdulai, 2016; Zhu et al., 2021). In addition, the Hausman test is used to confirm whether the variable of Internet use is endogenous, and the F-test is applied to test the weak IV problems. If the Hausman test rejects the null hypothesis, indicating that the IV estimation is better, and the F statistic value exceeds 10, it suggests that there are no weak IV problems in this study.

3.2.2 Data

This study uses data from the CHNS, which covers 10 waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015) in 12 provinces (Guangxi, Guizhou, Henan, Hubei, Heilongjiang, Hunan, Jiangsu, Liaoning, Shandong, Shaanxi, Yunnan and Zhejiang) and 3 autonomous cities (Beijing, Chongqing and Shanghai). A multistage random cluster design is used to select the CHNS sample. Specifically, one high-income city and another low-income city are first selected from each province. Following this sample strategy, CHNS selected two counties in each city, two urban communities, and two rural villages in each county. In each community and village, 20 households are randomly selected for participation. In this process, it included approximately 7,200 households and over 30,000 individuals as part of its longitudinal dataset. Note that CHNS includes a large number of questions about target family members and their food consumption, nutrition, and health-related questions, and it is one of the most widely used datasets for nutrition and health-related research (Yang & Bansak, 2020; Chen et al., 2019).

To fulfill the purpose of this study, two criteria are applied to the CHNS dataset. First, we only use a sample of respondents whose age is equal/or larger than 18 years old living in rural areas. Second, since the information on food consumption and dietary knowledge is only available from 2004 to 2011, we used respondents from this period for food consumption analysis and respondents from 2004 to 2015 for nutrition outcomes and health analysis. Finally, 27,390 observations and 11,292 individuals in 167 villages are obtained for analysis. Because this is unbalanced panel data, there are slight differences in the sample size of regression models with different dependent variables.

The dependent variable is Internet use. This is a dummy variable defined as 1 if the respondent uses the Internet and 0 otherwise.

The healthy eating index (HEI) for Chinese and the dietary diversity score (DDS) are used as the proxy variables of nutritional intake. HEI is designed as a scoring system to measure dietary quality and was recently developed by Yuan et al. (2017). According to the Dietary Guidelines for Chinese (DGC) in 2016, all food groups are divided into adequacy and limitation components. Adequate components include 12 food groups (total grains, whole grains, and mixed beans, tubers, vegetables, dark vegetables, fruits, dairy, soybeans, fish and seafood, poultry, eggs, and seed and nuts), and limiting ingredients include 5 food groups (red meat, cooking oils, sodium, added sugars, and alcohol). The DGC gave the maximum and minimum daily recommendations for the adequate and limited food groups, respectively. Then all food groups are weighted to a maximum of 5 or 10 scores, and HEI is the total score between 0 and 100. Higher HEI scores indicate better dietary health of respondents. For more details on the establishment of the HEI, please see Table A3.1 In this study, due to the lack of information on the daily intake of added sugars, the highest score for HEI is 95. As shown in Table 3.1, the mean value of HEI is 60.1, which is comparable to some literature (Ren et al., 2021; Yuan et al., 2017).

The dietary diversity score (DDS) is also widely used to calculate dietary quality (Cui et al., 2021), and it can be calculated as follows.

$$DDS_i = \begin{cases} 1, & if\ x_i > 0 \\ 0, & if\ x_i = 0 \end{cases}$$

$$Where\ x_i = \begin{Bmatrix} Total\ Grains\ ; Tubers\ ; Vegetables\ ; Fruits\ ; Dairy\ ; Soybeans\ ; \\ Fish\ and\ Seafood\ ; Poultry; Red\ Meat\ ; Eggs\ ; Seed\ and\ Nuts \end{Bmatrix} \tag{3-6}$$

$$DDS = \sum_{I=1}^{10} DDS_i \tag{3-7}$$

Where x_i is the daily food intake of food group i; the value of DDS_i is 1 if the respondent has eaten the i-th food in the last three days of the survey, otherwise DDS_i is 0. Finally, the DDS is the sum of all the food groups, ranging from 0 to 10. As shown in Table 3.1, the mean value of DDS is 4.824, which is similar to that of Shen et al. (2023). For more details on the consumption of each food group, please refer to Figure A3.3.

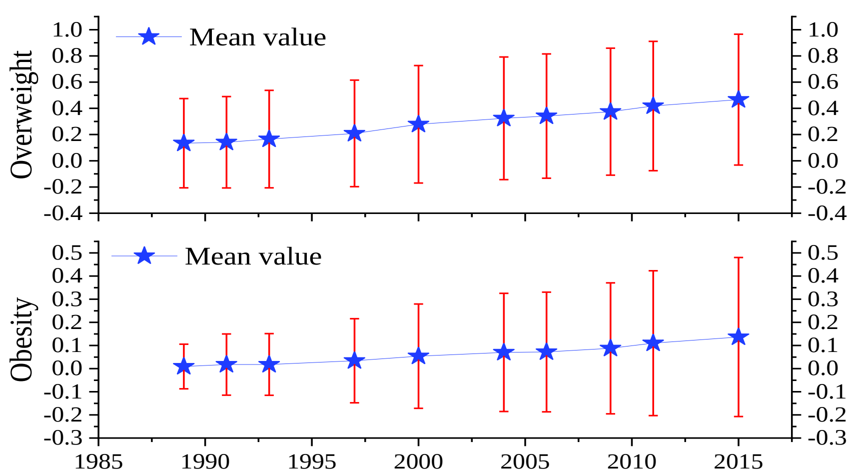

Figure 3.3: The trend of nutrition outcomes from 1989 to 2015 in rural China

Notes: The upper and lower endpoints are the mean plus or minus the standard deviation. Source: Authors' calculation based on the CHNS data from 1989 to 2015.

Four dependent variables are used in this study to measure health outcomes: overweight, obesity, self-assessment score of health, and chronic disease. The CHNS dataset contains the height and weight of the respondents and can be used to calculate the respondents' body mass index (BMI), which is weight divided by the square of height (in kg/m2). Following the existing literature, the respondents with a BMI equal to or greater than 24 are defined as overweight, and equal to or greater than 28 are defined as obese (Liu et al., 2021; Pan et al., 2021). The results in Table 3.1 show that the central values of overweight and obesity between 2004 and 2015 in rural China are 28.9% and 6.2%, which are similar to the findings of Ren et al. (2022). In addition, as can be seen from Figure 3.3, both the mean and standard deviation of overweight and obesity in rural China show an increasing trend. This means the obesity problem in rural China is becoming more and more serious, and the difference in obesity among residents is also increasing.

The self-assessment score of health is also widely used by many researchers (Smith & Goldman, 2011; Cullati et al., 2020; Maddox & Douglass, 1973). In the CHNS survey, one of the questions is how healthy do you think you are? The respondents have to choose a number from 1 to 10. However, many researchers argue that this variable is too subjective to obtain accurate health status information (Smith & Goldman, 2011; Althubaiti, 2016; Voukelatou et al., 2021). Thus, we also use whether the respondents had a chronic disease (diagnosed with high blood pressure and diabetes) as our measure of health variable. Indeed, we also believe that the second objective variable is more reasonable. However, in this study, we can further discuss whether the self-assessment score of health is a reliable variable to measure health status by comparing the regression results of the two dependent variables.

The dietary knowledge is calculated based on 12 questions assessing basic dietary knowledge. Referring to the criteria recommended by the WHO and the study by Ren et al. (2021). We constructed a brief index based on the respondents' answers: the correct answer is assigned a value of 1, and the wrong answer is assigned a value of -1, so the dietary knowledge ranges from -12 to 12. This measure has been widely used to assess an individual's dietary knowledge, and more details are presented in Table A3.2. A higher score indicates greater knowledge of food consumption and nutritional intake. As shown in Table 3.1, the average score of dietary knowledge is 6.117, and the average score of dietary knowledge in the Internet use sample is 1.979 points higher than that in the non-Internet use sample. The CHNS data also tracked the physical activities of the respondents. Specifically, CHNS data recorded respondents' participation in various sports over the past week, including martial arts (Kung Fu, etc.), gymnastics, dance, acrobatics, track and field (running, etc.), swimming, football, basketball, tennis, badminton, and volleyball. In this study, the physical activity variable is the number of types of activities that respondents had participated in in the past week, as shown in Table 3.1, which shows that the physical activities of Internet users are significantly lower than those of non-Internet users.

The control variables in this study include age, marital status, education, employment status, income, and household size. As shown in Table 3.1, the average age of Internet users is 35.9, which is well lower than that of non-Internet users of 42.8 years. We also controlled for the household income and respondents' level of education. First, there is a certain cost associated with using the Internet, considering the relatively lower income levels of the rural population in China. As income increases, the likelihood of using the internet may correspondingly increase. Secondly, most rural Chinese are exposed to the Internet later, and individuals with higher levels of education may be more inclined to learn and use the Internet. In addition, we also controlled the work status, marriage status, and household size. More detailed descriptive statistics of the main variables are presented in Table 3.1.

Table 3.1: The descriptive statistics of the main variables

Variables		**Pooled**	**Internet use**	**Non-Internet use**	**Diff.**
Dependent variables					
HEI	Healthy Eating Index for Chinese	60.647	62.100	60.408	1.692 ***
		(6.813)	(7.308)	(6.706)	
DDS	Dietary diversity score	4.824	4.366	4.896	-0.530***
		(3.129)	(3.461)	(3.052)	
Overweight	= 1 if overweight; = 0 otherwise	0.289	0.364	0.284	0.081***
		(0.453)	(0.481)	(0.451)	
Obesity	= 1 if obesity; = 0 otherwise	0.062	0.096	0.060	0.036***
		(0.242)	(0.294)	(0.238)	
Chronic	= 1 if chronic disease; = 0 otherwise	0.022	0.011	0.023	-0.012***
		(0.145)	(0.102)	(0.149)	
Health score	Self-assessment score of health	4.956	5.544	4.917	0.627***
		(2.284)	(2.611)	(2.256)	
Channel variables					
Knowledge	Dietary knowledge	6.117	7.821	5.842	1.979***
		(3.653)	(3.132)	(3.656)	
Activities	Physical activity	2.339	0.378	2.470	-2.092***
		(2.883)	(0.990)	(2.920)	
Control variables					
Age	Age of the respondent (years)	42.412	35.942	42.843	-6.902***
		(15.525)	(12.647)	(15.603)	
Marriage	= 1 if married; = 0 otherwise	0.817	0.795	0.819	-0.024***
		(0.398)	(0.404)	(0.398)	
Education	Education of the respondent (years)	7.518	12.257	7.194	5.062***
		(4.183)	(4.321)	(3.972)	
Work	= 1 if able to work; = 0 otherwise	0.860	0.884	0.859	0.025***
		(0.347)	(0.321)	(0.348)	
Income	Household income	8.836	9.930	8.763	1.167***
		(1.067)	(0.943)	(1.035)	
Family size	Number of family members	20.109	36.551	19.010	17.541***
		(28.541)	(46.882)	(26.512)	0.081

Notes: Diff is the T-test results and *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$. The standard deviation is in parentheses.

3.3 Results and discussion

3.3.1 The effect of Internet use on nutritional intake and health outcomes

The IV estimation results for the effect of Internet use on nutritional intake and health outcomes are presented in Table 3.2. The P value of the Hausman test is less than 0.001, and all the F-statistic values are greater than 10, which indicates that IV estimation strategies are necessary. The hypothesis of weak instrumental variables is rejected. The results with and without control variables are consistent, which further indicates that our estimates are robust.

Table 3.2: The effect of Internet use on nutritional intake and health outcomes

	HEI	**HEI**	**DDS**	**DDS**
Internet use	6.071***	1.987***	7.616***	0.572***
	(18.259)	(5.606)	(49.688)	(8.511)
Control variables	No	Yes	No	Yes
Wald chi2	1270.14***	8488.57***	333.40***	1758.30***
Observations	20679	20105	20679	20105
	Overweight	**Overweight**	**Obesity**	**Obesity**
Internet use	1.368***	0.263***	1.177***	0.196**
	(30.049)	(3.885)	(23.531)	(2.048)
Control variables	No	Yes	No	Yes
Wald chi2	902.97***	5890.29***	553.72***	2343.38***
Observations	26077	25366	26077	25366
	Chronic	**Chronic**	**Health score**	**Health score**
Internet use	0.286***	0.512***	2.150***	2.556***
	(3.319)	(3.618)	(24.554)	(19.356)
Control variables	No	Yes	No	Yes
Wald chi2	11.01***	837.52***	637.66***	5709.91***
Observations	27079	26485	27380	26563

The fixed effects are used to estimate the results, and the robust standard deviation is in parentheses. *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$.

As shown in the upper part of Table 3.2, Internet use can significantly increase HEI and DDS. Specifically, the mean values of HEI and DDS of Internet users are about 1.987and 0.572 higher, respectively, than those of non-Internet users. The estimated coefficients of results with control variables are larger than those without control variables, suggesting that the results may be overestimated if control variables are not taken into account. These results suggest that Internet use can improve dietary quality. The middle part of Table 3.2 is the estimated results for health outcomes. The coefficients of overweight and obesity are all positively significant at 1% level, which means the Internet could increase the overweight and obesity among adults in rural China. The coefficients of chronic are also positive and significant at 1% level, which suggests that respondents who use the Internet may have higher rates of high blood pressure and diabetes. Regression estimates of overweight, obesity, and chronic disease results suggest that Internet use may be harmful to health. However, the estimated effect of health scores indicates a positive relationship between Internet use and the self-assessment score of health, which may be due to a severe lack of awareness of the health risks of chronic diseases among Chinese rural residents.

3.3.2 The effect of Internet use on dietary knowledge and physical activity

The estimated results of dietary knowledge and physical activity are presented in Table 3.3. First, when the control variables are included, the estimated coefficient of dietary knowledge is 2.008 and is significant at the 1% level, indicating that Internet use can increase respondents' dietary knowledge. Generally speaking, the higher the dietary knowledge, the higher the level of dietary quality. Therefore, Internet use can improve dietary quality by improving dietary knowledge. Second, our estimated coefficient of physical activity is -0.117 and significant at the 1% level, indicating that Internet use significantly reduces respondents' physical activity, which further negatively impacts nutritional outcomes and health.

Our results suggest that the positive effects of Internet use may be smaller than the adverse effects in rural China. Therefore, the overall impact of Internet use on nutrition outcomes and the health of rural residents is negative. In particular, Internet use increases the likelihood of being overweight, obese, having high blood pressure, and diabetes.

Table 3.3: The effect of Internet use on dietary knowledge and physical activity

	Knowledge	**Knowledge**	**Activities**	**Activities**
Internet use	6.758***	2.008***	-1.658***	-0.117***
	(41.185)	(12.689)	(-35.639)	(-2.752)
Control variables	No	Yes	No	Yes
Wald chi2	1696.18***	28215.73***	1270.14***	8479.18***
Observations	26617	26100	27390	26563

The fixed effects are used to estimate the results, and the robust standard error is in parentheses. *** is p < 0.01; ** is p < 0.05; * is p < 0.1.

3.3.3 Heterogeneity analysis

Table 3.4: The heterogeneity analysis by gender

Male sample:			
	HEI	**DDS**	**Overweight**
Internet use	6.193***	0.917***	0.414***
	(10.923)	(9.467)	(4.526)
Wald chi2	2097.67***	181193.44***	3538.68***
Observations	9975	13378	12638
	Obesity	**Chronic**	**Health score**
Internet use	0.238*	0.350	2.580***
	(1.717)	(1.606)	(14.418)
Wald chi2	1124.26***	375.39***	2821.52***
Observations	12638	13339	13378
Female sample:			
	HEI	**DDS**	**Overweight**
Internet use	7.170***	1.109***	0.062
	(11.811)	(10.065)	(0.629)
Wald chi2	2241.70***	167359.59***	2566.24***
Observations	10130	13185	12728
Internet use	**Obesity**	**Chronic**	**Health score**
	0.087	0.674***	2.465***
Wald chi2	(0.613)	(2.966)	(12.678)
Observations	1090.06***	378.77***	3021.18***

The fixed effects are used to estimate the results, and the robust standard error is in parentheses. *** is p < 0.01; ** is p < 0.05; * is p < 0.1.

This section focuses on the heterogeneity of Internet use on nutritional intake and health outcomes across gender, age, and income. These results have been considered control covariates. First, we checked whether the baseline results of this study also apply to the male and female samples, and the specific estimates are shown in Table 3.4. The results show that Internet use has a significant positive effect on HEI and DDS in both male and female samples, which is consistent with our baseline regression results. However, there are apparent gender differences in the effect of Internet use on overweight and obesity. Specifically, Internet use significantly increased the probability of overweight and obesity for the male sample but had no significant effect on the female sample. Regression results for the two health variables revealed a positive relationship between Internet use and both chronic disease and self-assessment scores of health in both male and female samples. However, the estimated coefficient of Internet use for chronic disease in males was not significant.

Table 3.5: The heterogeneity analysis by age

Sample: Age < 45			
	HEI	**DDS**	**Overweight**
Internet use	1.001**	1.092***	-0.151
	(2.119)	(9.501)	(-0.996)
Wald chi2	624.62***	137921.09***	2777.10***
Observations	8281	10512	9779
	Obesity	**Chronic**	**Health score**
Internet use	0.034	-0.884	2.928***
	(0.346)	(-1.605)	(15.320)
Wald chi2	1044.53***	70.80***	3314.28***
Observations	9779	6810	10512
Sample: Age ≥ 45			
	HEI	**DDS**	**Overweight**
Internet use	8.600***	1.812***	0.709***
	(11.719)	(12.031)	(4.100)
Wald chi2	2460.51***	211548.79***	2783.07***
Observations	11824	16051	15587
Internet use	**Obesity**	**Chronic**	**Health score**
	0.767***	1.109***	3.566***
	(6.142)	(5.046)	(12.522)
Wald chi2	2460.51***	211548.79***	2783.07***
Observations	11824	16051	15587

The fixed effects are used to estimate the results, and the robust standard error is in parentheses. *** is p < 0.01; ** is p < 0.05; * is p < 0.1.

The second heterogeneity analysis strategy of this study is to analyze the differences in Internet use on nutritional intake and health outcomes across different age groups. As proposed by WHO, it defines young people as aged below 44 years old; middle-aged and elderly people are those aged over 45 years old. So, we defined those aged below 45 as the youth group and those aged 45 and above as the elderly group, with their respective results shown in Table 3.5. The estimated coefficients of the aged group are significantly positive and larger than those of the young group. Thus, Internet use is likely to have a greater impact on nutrition and health in the elderly age group than in the younger age group. Besides, in the youth group, the estimated coefficients of HEI, DDS, and Health score are significantly positive, while the estimated coefficients of overweight, obesity, and Chronic are not statistically significant.

Table 3.6: The heterogeneity analysis by income

Low-income group:			
	HEI	**DDS**	**Overweight**
Internet use	4.918***	1.231***	0.154
	(9.851)	(10.420)	(0.917)
Wald chi2	1165.83***	100363.52***	2275.99***
Observations	11087	13142	12591
	Obesity	**Chronic**	**Health score**
Internet use	0.358***	0.759***	2.442***
	(3.333)	(2.853)	(11.664)
Wald chi2	817.77***	126.54***	3048.09***
Observations	12591	13052	13142
High-income group:			
	HEI	**DDS**	**Overweight**
Internet use	9.600***	1.645***	0.388**
	(12.524)	(12.777)	(2.571)
Wald chi2	2360.37***	244113.28***	2473.74***
Observations	9018	13421	12775
Internet use	**Obesity**	**Chronic**	**Health score**
	0.393***	0.560**	3.718***
	(3.555)	(2.352)	(15.453)
Wald chi2	988.64***	581.13***	2644.37***
Observations	12775	13385	13421

The fixed effects are used to estimate the results, and the robust standard error is in parentheses. *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$.

As mentioned above, farmers with higher incomes are more likely to have access to the Internet. In this study, we defined the top 50 percent of the sample as a high-income group and the bottom 50 percent as a low-income group. The regressions of Internet use for nutritional intake and health outcomes across different income groups are shown in Table 3.6. We can see that the results for both income groups are consistent with the baseline results. There is a positive relationship between Internet use and HEI, DDS, overweight, obesity, and chronic health scores. However, in the low-income group, the regression coefficient of overweight is not significant. The regression coefficient of the variable Chronic in the high-income group is smaller than that in the low-income group. In comparison, the regression coefficient of the other variables is greater than that of the low-income group. Therefore, Internet use may have a greater impact on food consumption, nutritional outcomes, and health in high-income groups than in low-income groups.

In the past few decades, Internet penetration in China has risen rapidly. By the end of 2016, the number of Internet users in China had reached 731 million, placing the country first in the world, with an average annual growth rate of more than 40 million (6.2%) (Zheng et al.,2021). The rapid development of the Internet has changed people's food consumption patterns and living habits (Li et al.,2021). These changes have further affected the population's food consumption, nutritional outcomes, and health status. As shown in Figure 3.2, China's Internet users are comparable to the world average level. Moreover, China is the largest developing country in the world, and findings such as the effects of Internet use on nutritional intake and health outcomes in its rural areas may have some implications for other developing countries. While the use of the Internet is also skyrocketing in developing countries such as India, Vietnam, and Thailand, and the quality of diet is improving, nutritional health is an important issue for all developing countries. Therefore, the results of this study may have important reference significance for policymakers not only in China but also in other developing countries. In addition, despite significant differences in economic and social development levels, dietary structures, and other factors between China and European and American countries, the influence channels of Internet use on nutritional intake and health outcomes may be consistent. In this study, the influence channels of diet quality and physical activity have been verified, which can also be used as a reference for the research on Internet use and nutrition and health in developed countries.

This study found that Internet use significantly improved dietary quality, as measured by HEI and DDS, which is consistent with the findings of existing literature. For example, Xue et al. (2021) found that Internet access significantly increased protein intake, which could be conducive to improving dietary quality. Ma and Jin found that there is a positive relationship between Internet use and a healthy diet. Cui et al. (2023) argued that Internet use can improve family dietary quality, as evidenced by the Chinese Diet Balance Index (DBI). In rural China, the reasons why Internet use can improve dietary quality may be mainly due to the following two points. First, the Internet is one of the main ways to obtain nutrition and health knowledge, especially in rural areas. Therefore, Internet use can improve dietary quality by improving dietary knowledge. Second, the rise of online shopping can help rural residents buy food that is not available in nearby markets, improving food availability. Therefore, Internet use may have a significant positive impact on dietary quality.

Another important finding of this study is that Internet use increases the risk of overweight and obesity among rural Chinese residents. This finding is consistent with the findings of Corneel et al. (2009). They believe that Internet use increases the likelihood of overweight and obesity among Australian students because it increases the amount of time spent watching TV and being sedentary. However, our results are contrary to those of Chen and Liu (2022), who concluded that Internet access increases the income of urban residents and thus reduces their risk of being overweight. This difference may be due to systematic differences in income structure, living habits, and dietary intake between rural and urban residents. Previous studies also found that the relationship between income and nutrition outcomes is opposite in rural and urban China (Bakkeli, 2016; Ren et al., 2019). We also found that one of the important reasons that Internet use increases the risk of overweight and obesity is due to a reduction in the frequency of physical activity among respondents. One interesting finding is that for young adults and females, Internet use will not increase their risk of being overweight and obese. It is possible that younger, younger, and female groups are more concerned about weight management than male and older age groups. It is worth noting that current articles on Internet use in developing countries primarily focus on urban areas and mainly study the positive effects of Internet use on food consumption and nutritional intake. Therefore, our findings are an important supplement to the existing literature.

This study finds that there is a positive relationship between Internet use and the self-assessment score of health, which is consistent with the results of Luo et al. (2024). Besides, Ding et al. (2023) also argue that the Internet is beneficial to mental health. However, Ma and Sheng (2023) find that Internet use may reduce duration and parent-adolescent communication, thus hurting their mental health. Therefore, the impact of Internet use on different countries and groups may vary. At the same time, we also find that Internet use increases the likelihood of chronic disease. It can be explained as similar to overweight and obesity, in that Internet use reduces physical activities. Considering that these three variables of overweight, obesity, and chronic disease are more objective than the Health score, we argue that Internet use improves diet quality, whereas it reduces physical activity; Internet use hurts the health of rural residents. Therefore, Internet use has both positive and negative effects on the nutrition and health of Chinese rural residents.

There are some limitations in this study. First, due to data limitations, we only used hypertension and diabetes to measure chronic diseases. However, follow-up studies could use other chronic conditions to measure health, such as anemia or hyperlipidemia. In the past two decades, some chronic diseases, such as overweight and obesity, have proliferated in China, rising rapidly from a long-term level lower than the world level to a level higher than the world level. Second, the data in this study span from 2004 to 2015, a period that includes the 10 years with the fastest development of the Internet in China. It would be preferable for subsequent studies to utilize panel data from more recent years.

3.4 Conclusion

A series of studies have discussed the effect of Internet use on food consumption. However, the impact of Internet use on nutritional outcomes and health is little known, especially in developing countries such as China. Using multiple years of CHNS data and regression analysis, this study finds that Internet use improved dietary quality, such as HEI and DDS, among Chinese rural residents. However, Internet use may increase the risk of overweight, obesity, and health problems in the study regions. One important reason is that Internet use reduces their physical activity. The study also finds that the impact of Internet use on overweight and obesity is not significant among women and young people.

Given the rapid increase in the number of Internet users and the changing lifestyle (e.g., e-commerce) in Chinese rural areas, it is suggested that policymakers may seriously take its adverse effects into account when promoting the development of the Internet. For instance, increase investment in Internet infrastructure, allocate more physical facilities to rural communities, and provide dietary knowledge to cultivate awareness of nutritional self-care among males and older relatives who use the Internet. Insights and experiences from the study may also be valuable for the nutritional well-being of those developing regions in the digital era.

Chapter 4 The Effect of Internet Use on Sustainable Food Consumption[8]

4.1 Introduction

The foremost challenges confronting humanity include climate change and sustainable development, and current food consumption patterns are significantly exacerbating these issues (Asvatourian et al., 2018). The United Nations Sustainable Development Goals (SDGs) represent a global agreement on social, economic, and environmental targets that humanity aims to reach by 2030 (Chen et al., 2022). The global transition to environmentally friendly and nutritionally adequate sustainable food consumption will be key to achieving several SDGs simultaneously. On one hand, the Global Burden of Disease Assessment (GBD 2019 Disease Injury Collaborators, 2020) reports that more than 2 billion people are undernourished, and a poor diet is a leading cause of premature death and disease. On the other hand, food production processes contribute to environmental issues such as greenhouse gas emissions, freshwater scarcity, land degradation, and biodiversity loss. These environmental impacts could impede progress on SDG 6 (clean water and sanitation), SDG 13 (climate action), SDG 14 (life below water), and SDG 15 (life on land). Addressing these challenges remains formidable, as the diets of most people worldwide either lack essential micronutrients, impose high environmental costs, or exhibit both issues (Chen et al., 2022)

China is one of the largest food carbon emitters in the world, emitting 1.9 billion tons of CO2 equivalent in 2020 (He et al., 2018). Additionally, China's per capita water resources amount to only 25% of the global average, placing it among the 13 countries identified by the United Nations as facing severe water shortages (Wu et al., 2022). Between 1987 and 2017, China's per capita

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daily calorie intake from vegetables increased by 12%, while meat consumption surged by 198% (Hu et al., 2022; Xiong et al., 2020). Given that plant-based food chains generally have lower carbon and water footprints than animal-based food chains (Heller & Keoleian, 2015; Vermeulen et al., 2012), this dietary shift toward higher meat consumption places additional pressure on water resources and challenges China's emission reduction goals. Further, evidence shows that China’s food-related water and carbon footprints nearly tripled from 1961 to 2017, underscoring the need for policymakers to prioritize strategies that reduce these environmental footprints and support sustainable food consumption (Asvatourian et al., 2018; Xiong et al., 2020).

Most prior research focuses on quantifying the environmental footprints of food and assessing consumers' willingness to pay for food labels. At the same time, relatively few studies examine sustainable food consumption from the perspectives of consumer behavior and digital transformation. Internet use, however, reshapes food access patterns, broadening the range of available food and enhancing accessibility for consumers (Ren et al., 2020). Moreover, the Internet lowers transaction costs in agricultural markets, promotes farmers' market participation, and increases food affordability for consumers (Liu et al., 2021a). Zamani et al. (2024) find that the Internet also fosters competition within agricultural markets, which influences food prices and consumer behavior. As a primary information source, the Internet use shapes public attitudes toward environmental protection and affects food consumption preferences. These shifts may increase the intake of plant-based foods in rural areas, potentially influencing the environmental footprints of food consumption. However, further empirical studies are needed to clarify whether Internet use ultimately has a positive or negative impact on the environmental footprints of food consumption.

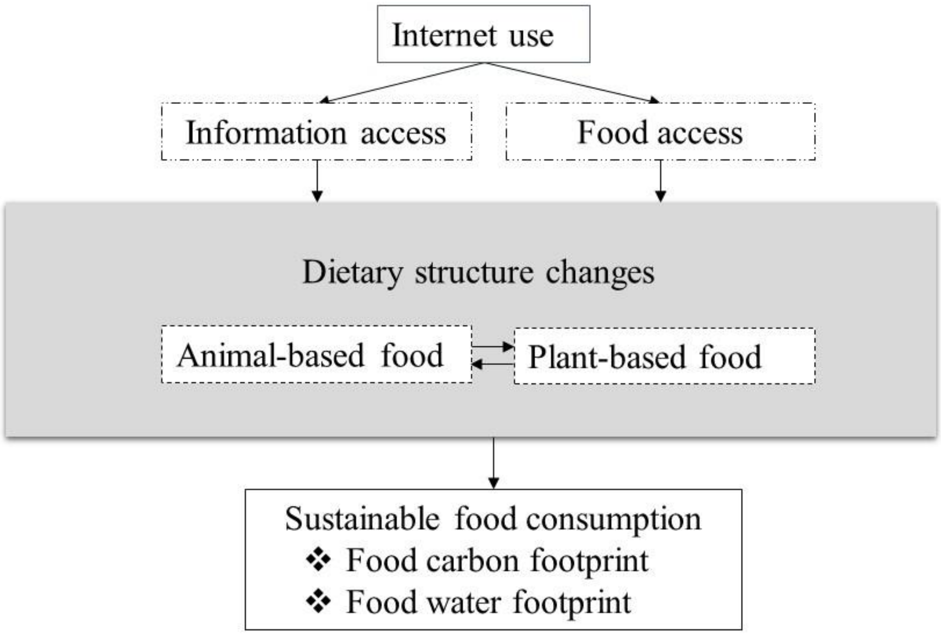
The purpose of this study is to explore the potential impact of Internet use on sustainable food consumption. This study has the following three contributions. First, this study contributes to existing literature by investigating the effect of Internet use from the perspective of consumption behavior. Our research can extend these two research topics of Internet use and sustainable food consumption. Second, we not only analyze the causal relationship between Internet use and sustainable food consumption, but also discuss the potential channels through which Internet use affects sustainable food consumption and its heterogeneity. The results show that Internet use reduces the food carbon footprints by 18.1% and food water footprints by 10.6%, primarily due to a reduction in the consumption of animal-based products such as pork and eggs. These findings could provide new lessons for achieving sustainable food consumption. Finally, we primarily focus on the impact of Internet use on sustainable food consumption in rural areas of China, thereby addressing the gap in research that primarily focuses on developed countries. It is worth noting that by the end of 2016, the number of Internet users in China reached 731 million, ranking first in the world. Given the rapid growth of Internet use in many developing countries, achieving sustainable food consumption is a common goal (Ma & Jin, 2022; Ren et al., 2021). The results of this study are expected to provide important policy implications for sustainable development in China. They may also provide valuable insights for other developing countries such as India, Vietnam, and Thailand.

A large body of literature examines the environmental impacts of diets, particularly in terms of food carbon and water footprints, as well as dietary patterns and footprints accounting. Kanemoto et al. (2019) find that while meat consumption weakly explains differences in household carbon footprints, reducing meat intake can decrease food carbon footprints across all Japanese households. Similarly, Albert et al. (2020) argue that restricting red meat and dairy consumption can reduce household carbon emissions, especially in larger urban areas. Vanham et al. (2021) investigate food consumption and water use in northern European cities, finding that a healthy diet with less meat can reduce the food water footprint. As urbanization increases, food consumption patterns in rural areas also shift, which affects the food water footprints. Das et al. (2021) conducted a study in India and found that the total food and water footprints rise with increased consumption of animal-based foods. Liu and Savenije (2008) offer international comparisons, noting that while China's food-related water use has tripled over the past 30 years, it remains lower than in most developed nations. Sommer and Kratena (2017) divide income into five levels and find that the carbon footprints of Europe's lowest income group are more than 2.5 times lower than the average per capita footprints (15.7 tonnes of carbon), while the footprints of the highest income group are just under twice the average. Using data from the Global Diet Database (GDD) and the Food and Agriculture Organization (FAO), Yin et al. (2024) find that global annual greenhouse gas emissions from food aging will reach 288 million tons of CO2 equivalent by 2100. Xu et al. (2013) reach a similar conclusion by analyzing food and water footprints. In general, research indicates that with population growth, urbanization, and rising incomes, diets shift from plant-based to animal-based foods. Since animal products, particularly red meat and dairy, generate significantly higher carbon emissions and water consumption than plant-based foods, these dietary shifts can lead to greater environmental impacts.

While these studies examine various factors influencing food carbon and water footprints, they remain limited, particularly in their lack of focus on how Internet usage affects sustainable food consumption. First, the Internet provides extensive information on the health benefits of plant-based diets, encouraging people to reduce their consumption of animal-based foods and incorporate more fruits, vegetables, and grains. For example, Internet use offers information about the negative environmental impacts of certain foods and exposes consumers to pro-environmental food choices (Obringer et al., 2021; Ren et al., 2019; Zhang et al., 2019b). Second, unlike conventional information channels such as television, newspapers, and broadcasts, the Internet offers a vast repository of information without the constraints imposed by specific publishers, and all at minimal cost. Internet use can improve market efficiency and affect food prices, as mobile coverage reduces search and transaction costs (Zamani et al., 2018). Consequently, the promotion and sale of whole grain foods and low-carbon labeled foods primarily occur online (Salahuddin et al., 2016; Zhang et al., 2019a). Third, studies indicate that information technology (Vatsa et al., 2023), particularly through social media, enhances public awareness of environmental risks and influences attitudes toward environmental protection, thereby promoting the consumption of plant-based foods. Gong et al. (2020) find that Internet use actively promotes environmentally friendly behavior at the individual level. Wang and Hao (2018) emphasize the Internet's role in providing tools to calculate food carbon emissions, enabling individuals to transition from environmentally friendly attitudes to sustainable behaviors, such as reducing the consumption of animal-based foods and selecting products with low-carbon labels. Huang and Tian (2019) discovered that Internet users are more likely to pay for food with environmental footprint labels, supporting the development of sustainable food consumption habits.

The Internet transforms the way people access food and serves as a primary channel for acquiring dietary knowledge. On one hand, the rise of food delivery services and online grocery shopping makes plant-based alternatives more accessible. Many platforms now offer vegan and vegetarian options alongside traditional choices, leading to an increase in plant-based food purchases (Gibin et al., 2022). However, many popular food delivery options, such as fast-food chains, heavily feature animal-based items on e-commerce platforms (Cheng et al., 2022). This ease of access can lead people to order animal-based foods for convenience, particularly in regions where plant-based options are limited. Overall, Internet use encourages greater openness to plant-based diets, primarily through social media, digital communities, and environmental information. However, the Internet also promotes the consumption of animal-based foods through trends like high-protein diets, food delivery options, and cultural dietary content. At the same time, literature indicates that Internet use is associated with agricultural productivity (Zhu et al., 2021), improved nutritional intake (Deng et al., 2024; Ma & Jin, 2022), increased income, reduced income inequality (Ma et al., 2018), and the adoption of sustainable agricultural practices. However, the effects of these factors on food carbon and water footprints remain unclear (Muange & Ngigi, 2021).

However, Internet use may also have some adverse effects on sustainable food consumption to some extent. For example, Vatsa et al. (2023) observe that Internet users are more inclined to order takeout, often choosing fast food and snacks, which frequently consist of animal-based products that significantly contribute to environmental degradation. Furthermore, misleading information is prevalent on the Internet (Obringer et al., 2021; Vatsa et al., 2023). Food advertising may often emphasize flavor and nutritional aspects while overlooking the negative environmental impact of food (Gong et al., 2020). For example, many advertisements for red meat, known for its high carbon footprint, often depict natural environments, creating a false impression of a low carbon footprint. As a result, the effect of Internet use on food consumption and its environmental consequences is mixed. This study examines the impact of Internet use on food consumption and its environmental footprints. Our research aims to expand the scope of investigations into food consumption and environmental footprints while exploring new approaches to mitigate the environmental effects of food consumption. Given the limited presence of grocery stores and supermarkets in rural China, which results in restricted food variety and compromised dietary quality, Internet use may have a more significant effect on farmer residents. Therefore, our study focuses on rural areas with farming communities. The theoretical framework illustrating the impact



of Internet use on food consumption and its environmental footprints is presented in Figure 4.1.

Figure 4.1: Theoretical framework

4.2 Method and Data

4.2.1 Method

To examine the effect of Internet use on sustainable food consumption, we initiate the investigation with the following benchmark models:

$$Y_{it} = \alpha_0 + \alpha_1 Internet_{it} + \alpha_2 X_{it} + \varepsilon_{it}, \quad (4\text{-}1)$$

where Y_{it} is the dependent variable in year t for the i-th individual, including the food carbon footprints and food water footprints; $Internet_{it}$ is the key independent variable. It is a dummy variable, while alpha sub 1 is the difference in environmental footprints between Internet users and non-users X_{it} represents the control variables, including age, education, marital status, work, household income, and household size; and ε_{it} is the error term.

When the $Internet_{it}$ is treated as an exogenous variable, α_1 in Equation 4-1 can be utilized to assess the effect of Internet use on food environmental footprints. However, the potential endogeneity may introduce biased and inconsistent estimates due to unobserved heterogeneity and self-selection bias. For example, certain studies have shown that people with higher levels of education and income are more likely to express a preference for Internet use (Ma et al., 2018). Other studies also find that education and income play crucial roles in influencing individuals' dietary intake (Du et al., 2004; Popkin & Ng, 2007). Note that the individual awareness of environmental protection is often challenging to quantify and is not included in our data. Therefore, overlooking the endogeneity of Internet use in food consumption might introduce bias into the estimation results.

The instrumental variable estimation is used to calculate the effect of Internet use on food environmental footprints. The number of residents using the Internet in the same village is used as an instrumental variable in this study. It should be noted that this instrumental variable has been widely used in existing studies (Ren et al., 2020; Zhao et al., 2014; Liu et al., 2023), and the two-stage least squares procedure is as follows:

$$Internet_{it} = \beta_0 + \beta_1 IV_{it} + \beta_2 X_{it} + \tau_{it}, \tag{4-2}$$

$$Y_{it} = \gamma_0 + \gamma_1 \widehat{Internet}_{it} + \gamma_2 X_{it} + \varphi_{it}, \tag{4-3}$$

where IV_{it} denotes the instrumental variable; X_{it} represent control variables; and $\widehat{Internet}_{it}$ is the predicted value of $Internet_{it}$ in Equation 4-2, ensuring it is not correlated with φ_{it}. γ_1 provides a consistent estimate of the impact of Internet use on food environmental footprints.

The proportion of the Internet use sample to the total village sample, excluding the household itself, serves as a good instrument for Internet use for two main reasons. First, it is expected to influence individual Internet use, particularly in rural areas directly. In China, residents within the same village are closely interconnected, and Internet use often shows a replicative effect among neighbors (Sun et al., 2023). Second, it could be considered an exogenous variable, as its influence on individuals' food consumption is limited to determining whether they use the Internet. Since all samples are randomly selected, and the number of responders in each village is approximately equal, this study treats the proportion of the Internet use sample to the total village sample as a reliable proxy variable for Internet use at the village level (Ma & Abdulai, 2016).

This study uses a Hausman test to assess the endogeneity of the variable. If the test is rejected, it implies that the regular estimate results may be biased. Besides, when the instrument is weak, the estimator remains biased, and the reliability of the Wald test is compromised. To evaluate the validity of the instrument variable, the study employs the Cragg-Donald Wald test and the F test to check for weak instrument issues. As a general guideline, if the value of the F statistic exceeds 10, concerns about the weak instrument problem are alleviated (Ren et al., 2019). Alternatively, Anderson–Rubin test could be accepted if there is only one endogenous variable.

4.2.2 Data

Data used in this study are from the CHNS, an international collaboration between the National Institute of Nutrition and Food Safety of the Chinese Center for Disease Control and Prevention and the Carolina Population Center at the University of North Carolina in Chapel Hill. Spanning 10 waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015), the CHNS covers 12 provinces (Jiangsu, Liaoning, Shandong, Shaanxi, Guangxi, Henan, Hubei, Hunan, Guizhou, Yunnan, Zhejiang and Heilongjiang) and 3 autonomous cities (Shanghai, Beijing and Chongqing), comprising approximately 7,200 households and over 30,000 individuals as part of its longitudinal dataset. The CHNS dataset contains extensive individual and household information, encompassing factors such as economic development, geography, public resources, health, and other indicators for the respondents. Furthermore, comprehensive community data have been collected through surveys involving food markets, health facilities, family planning officials, and other social service and community leaders. Renowned for its richness, the CHNS database stands as one of the most widely utilized Chinese databases in the realms of economics and nutrition research.

For this study, we used two criteria to narrow the sample range. Since 2004, the contents of the food consumption section of the CHNS questionnaire have remained consistent. However, the food intake of responders is not available in CHNS 2015 (information other than that on food consumption is published). Thus, only data from the 2004–2011 waves are used in this study. Second, we only consider adults (older than 18 years at the survey year) and restrict the sample to rural areas. Finally, 20,105 observations in 167 villages are obtained.

The key independent variable is Internet use. We assign a value of 1 to this dummy variable if the respondent uses the Internet, and a value of 0 if the respondent does not use the Internet.

This study assesses the environmental effects of diet structures based on practical concerns related to food production and consumption, using food carbon and water footprints. These footprints are determined by multiplying food consumption (both purchased and self-produced) by the corresponding weighted environmental intensities, calculated through the Life Cycle Assessment (LCA) method. Specifically, we extract carbon and water footprint factors for each food group from over 100 LCA studies, encompassing the entire life cycle from cradle to farm gate (Zhang et al., 2023). As shown in Table A4.1, the carbon LCA factor and water LCA factor in this study are the average values of these studies. Furthermore, CHNS also collects respondents' intake data for various food groups over the past three days, along with detailed nutritional information from the Chinese Food Composition Tables. We can calculate the average daily intake for each food group for each person (Muange & Ngigi, 2021; Yuan et al., 2017). Consequently, the carbon and water footprints can be computed using Equations 4-4 and 4-5, respectively:

$$CF_i = \sum_{j=1}^{n} f_j * Q_J, \tag{4-4}$$

$$WF_i = \sum_{j=1}^{n} w_j * S_J, \tag{4-5}$$

where CF_i and WF_i are the food carbon and water footprints for the i-th individual; f_j and w_j are the intakes of the i-th food group; Q_J and S_J are the weighted carbon intensity (g CO2e/g food) and weighted water intensity (g/g food) respectively. It should be noted that differences in cooking methods across regions and ethnic groups are not considered in this study, but we have compared the relevant research literature, and the findings show that our results are consistent with it (GDB 2017 Diet Collaborators, 2019; Hu et al., 2022). In addition, time and individual fixed effects are controlled for in the estimation of the parameters; hence, we believe that excluding these phases will not significantly change the outcomes.

In this study, dietary intakes include the 11 food groups of eggs, pork, poultry, red meat, fish and seafood, dairy, fruits, vegetables, tubers, beans, and grains. The per capita daily carbon and water footprints of each food group in rural China in 2004–2011 are shown in Figure 4.2. As depicted in Figure 4.2, there is no notable shift observed in the ratios of the carbon and water footprints among different food groups in rural China from 2004 to 2011. However, substantial variations exist in the overall contributions of various food groups to the carbon and water footprints. The food carbon footprints of China's rural areas come mainly from red meat consumption, which exceeds 50% of the total food carbon footprints and shows an increasing trend. Red meat, eggs, and grain consumption mainly produce the food water footprints. This suggests that if the Chinese could reduce their meat consumption, especially in terms of red meat, the environmental impact of their diet would be significantly reduced.

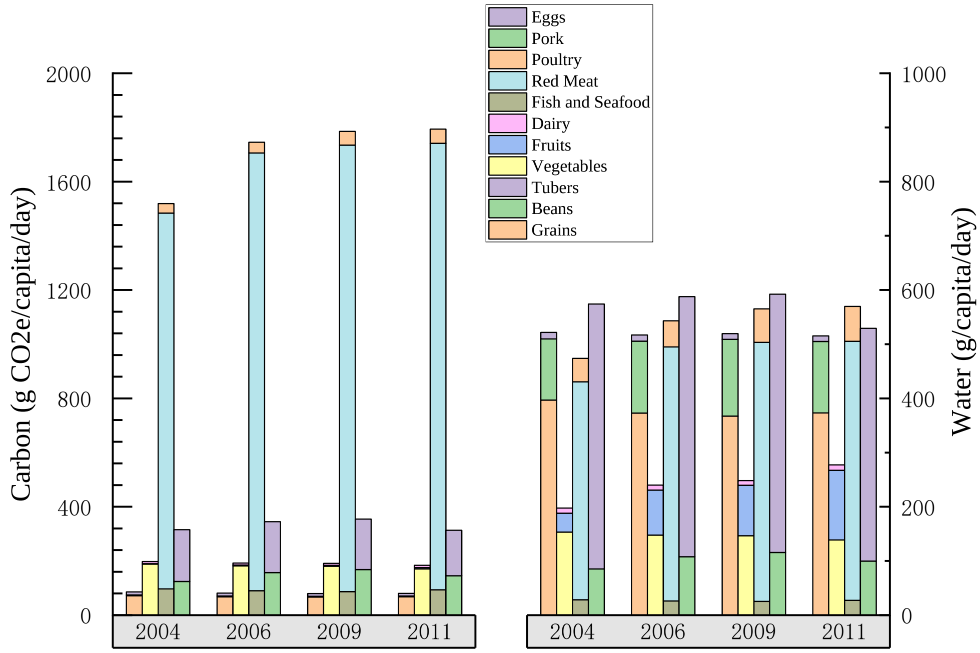


Figure 4.2: Food carbon footprints and food water footprints in rural China

Notes: Per capita daily average dietary carbon footprints (unit: g CO2e/capita/day) and water footprints (unit: g/capita/day) of food groups in rural China in 2004–2011.

The average dietary carbon footprints and water footprints from 2004 to 2011 for Internet users and non-users are shown in Figure 4.3. Between 2004 and 2011, the median and mean carbon and water footprints of Internet users were consistently higher than those of non–users. However, an overall decreasing trend is evident in the mean and median food carbon footprints of Internet users; there is also a decreasing trend in the food water footprints, but this is not as great as the decrease in the food carbon footprints. For non–users, the median and mean food carbon and food water footprints show an increasing trend. It is essential to highlight that we currently do not control for the individual and household characteristics of respondents in this analysis, and we are not addressing the endogeneity of Internet use either. Therefore, further results are needed to identify the causal effects of Internet use on the environmental footprints of food.

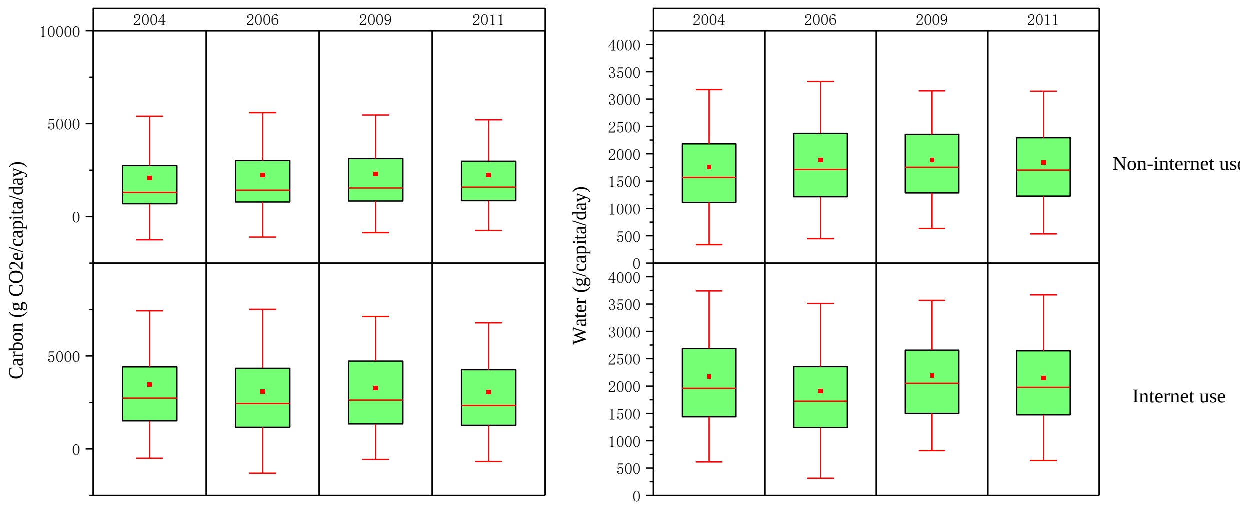


Figure 4.3: Food environmental footprints for Internet-use and non-Internet-use groups

Notes: Dietary carbon footprints (in gCO2e/ per capita/day) and water footprints (in g/capita/day) in rural China for Internet-use and non-Internet-use groups. The boxplots display the median, first quantile, and third quantile values for the food carbon and water footprints, with the point representing the mean value.

We controlled the age of respondents because the probability of Internet use and dietary intake may change with age. As indicated in Table 4.1, the mean age of Internet users is 35.6 years, while the mean age of non-Internet users is 48.6 years, with a significant difference at the 1% level. Education and income serve as additional control variables. First, most Chinese adults encounter the Internet later in life, and those with higher education levels are more likely to learn and use it. Second, as Internet use comes with a certain cost, an increase in income is associated with a higher likelihood of using the Internet. Additionally, at the individual level, we control for marriage status, work status, and household size. Household size is considered to account for heterogeneous effects on dietary intake and Internet use at the household level. All the control variables are selected with reference to the existing literature. More detailed descriptive statistics on the main variables are provided in Table 4.1.

Table 4.1: The descriptive statistics of main variables

Variables	Definition	Pooled	Internet-use	Non-Internet-use	Diff [a]
		(1)	(2)	(3)	(2)-(3)
Independent variables					
Internet use	1 if use Internet, 0 otherwise	0.161 (0.368)			
Dependent variables					
Carbon	Food carbon footprints (unit: g CO_2e/capita/day)	2315.650 (2223.040)	3151.150 (2652.508)	2208.940 (2138.760)	942.210***
Water	Food water footprints (unit: g/capita/day)	1867.907 (922.527)	2095.184 (1012.947)	1838.879 (906.266)	256.305***
Control variables:					
Age	Age of the respondent (year)	47.102 (14.528)	35.586 (13.210)	48.573 (14.023)	-12.987***
Marriage	=1 if married, =0 otherwise	0.886 (0.317)	0.767 (0.423)	0.901 (0.298)	-0.134***
Education	Education attainment (year)	8.067 (4.211)	12.050 (4.436)	7.558 (3.898)	4.492***
Work	=1 if working, =0 otherwise	0.779 (0.415)	0.900 (0.299)	0.764 (0.425)	0.137***
Income	Household per capita income (unit: CNY)	15348.450 (17991.360)	25647.490 (24531.380)	14033.060 (16520.370)	11614.43***
House size	Number of families	4.060 (32.177)	3.742 (35.995)	4.087 (31.638)	-0.345***
No. of observations:		20105	3237	16868	

Notes: Standard deviations are provided in parentheses; *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$. [a] T-test has been employed.

4.3 Results and Discussion

4.3.1 IV estimation results

The IV estimation results for the impact of Internet use on food carbon and water footprints are presented in Table 4.2. The Hausman test of endogeneity, which assesses the validity of the instrumental estimation model, rejects the null hypothesis regarding the exogeneity of Internet use at the 1% significance level. This indicates that the IV estimation is the appropriate model for further analysis. The significant coefficient of the IV at the 1% level suggests that as more people in the village use the Internet, respondents are more likely to use it as well.

Table 4.2: Effect of Internet use on food environmental footprints

	Carbon [a]		Water [a]	
	First stage	**Second stage**	**First stage**	**Second stage**
Internet use		-0.181***		-0.106***
		(0.058)		(0.032)
Age	-0.010***	0.006**	-0.010***	0.009***
	(0.001)	(0.002)	(0.001)	(0.001)
Marriage	0.016	0.090**	0.016	0.024
	(0.011)	(0.045)	(0.011)	(0.025)
Education	0.004***	-0.004	0.004***	-0.001
	(0.001)	(-0.420)	(0.001)	(0.500)
Work	0.024***	-0.003	0.024***	0.002
	(0.006)	(0.02)	(0.006)	(0.011)
Income [a]	-0.001	0.065***	-0.001	0.027***
	(0.002)	(0.010)	(0.002)	(0.005)
Household size	0.000	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.412***	6.438***	0.412***	6.688***
	(0.036)		(0.036)	
IV	0.017***		0.017***	
	(0.000)		(0.000)	
Endogeneity test p-value		0.000		0.000
F test		2925.180		2925.18
Cragg–Donald Wald test		5298.514		5298.514
weak instrumental test		16.380		16.380
Anderson–Rubin (AR) test		363.640 (0.000)		7.490(0.006)
R-squared	0.323	0.002	0.323	0.009
Observations	20105	20105	20105	20105

Notes: *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses; [a] natural logarithm is used for regression.

Additionally, Internet use at the village level generally influences individual production and consumption behavior by determining whether individuals use the Internet (Ma et al., 2018; Popkin & Ng, 2007). Despite the exogenous correlation of this instrumental variable with Internet use, its validity is tested to ensure that the instrument is not weak. As shown at the bottom of Table 4.2, both the F-test and the Cragg–Donald Wald test values exceed the critical value of 10. Therefore, there is no significant concern regarding the presence of a weak instrument problem in this estimation (Ren et al., 2019a).

In the first stage results, the coefficient for age is negative and significant at the 1% level. This can be explained by the fact that older individuals are less inclined to use the Internet. These results are consistent with some existing studies (Deng et al.,2024; Zhu et al., 2021). Notably, China's Internet user base has witnessed rapid growth only in the past two decades, extending from urban centers to rural areas. Some elderly individuals in rural China have already adapted to a life without the Internet and display less enthusiasm for embracing new technologies (Liu et al., 2019). Hence, there may exist a negative relationship between age and Internet use.

The coefficients for both education and work status are positive and significant at the 1% level. This indicates that respondents with higher levels of education are more inclined to use the Internet, and individuals with jobs are more likely to use the Internet compared to those without jobs. These findings align with existing literature (Briggs & Chowdhury, 2018; Han et al., 2023; Ren et al., 2022). Public courses in schools often incorporate Internet-related topics, and individuals with higher education levels typically have better access to the Internet. Moreover, respondents with higher education levels tend to possess better learning abilities, making them more likely to embrace and use the Internet.

In the second stage results, coefficients of Internet use on food carbon footprints and food water footprints are -0.181 and -0.106, respectively, and significant at the 1% level. That suggests that Internet use has the potential to decrease carbon footprints by approximately 18.1% and water footprints by about 10.6%, holding other conditions constant and addressing endogeneity. These results align with our expectations.

On one hand, the Internet provides a wealth of information about the health benefits of plant-based diets, which can encourage people to reduce their consumption of animal-based foods and incorporate more fruits, vegetables, and grains (Kashyap & Agarwal, 2020; Wolf et al., 2011). On the other hand, Internet use increases public awareness of environmental risks and influences attitudes toward environmental protection, which further promotes the consumption of plant-based foods. Since plant-based food chains have lower carbon and water footprints than animal-based food chains (Macdiarmid et al., 2012; Xue et al., 2021), the Internet can contribute to sustainable food consumption by reducing food carbon and water footprints. Furthermore, Internet use improves agricultural market performance and pricing, which serves as another important channel through which the Internet supports sustainable food consumption (Zamani et al., 2024).

The coefficients of age concerning food carbon and food water footprints are 0.006 and 0.009, respectively, and significant at the 1% level. This suggests that for each year of reduction in average age, the food carbon and food water footprints would be reduced by 0.6% and 0.9%, respectively. Studies find that an increasing number of young people are willing to buy organic and environmentally certified food to reduce carbon emissions and water consumption in the food production process (Goossensen et al., 2023; Treu et al., 2017). Studies have also found that young people are more inclined to choose locally sourced ingredients to reduce the carbon footprints caused by long-distance transportation (Shen et al., 2020). This environmentally friendly food choice reflects not only young people's awareness of consumption but also their sense of responsibility for environmental issues. Besides, this study found that young people are more inclined to choose vegetarian and plant-based foods, which reduces the demand for carbon- and water-intensive foods to some extent, thereby reducing their food carbon and food water footprints (Long et al., 2022). As shown in Table 4.2, income is also significantly positive. This suggests that, as incomes rise, the food carbon and water footprints increase. In rural areas of China, certain foods with high carbon emissions and high water consumption, such as beef, pork, fish, and milk, tend to have higher prices, limiting their consumption among rural residents. As incomes increase, the intake of these foods also increases, which raises the food carbon and water footprints. The coefficients of marriage and household size are also positive. One explanation for this could be that married families and larger families often have more social activities and meals, which can lead to more food waste and overconsumption, thereby increasing the food carbon and water footprints.

4.3.2 Robustness check

To examine the robustness of our main findings, we conduct two additional analyses using different methods to address the endogeneity problem of Internet use. First, we use the propensity score matching (PSM) method to address potential endogeneity arising from self-selection bias due to observable factors. The results are presented in columns (1) and (2) of Table 4.3. It shows that the effect of Internet use on the environmental outcomes of food consumption is mainly consistent with the estimate presented in Table 4.2, although the magnitudes differ. The possible reason is that PSM can only partially deal with the endogeneity problem if there is self-selection bias due to observable factors; the estimates from PSM may be biased. Fortunately, the IV estimation method can address the endogeneity issue caused by both observable and unobservable variables. To further validate the reliability of the IV estimates, we use an alternative instrument variable to test the robustness of our results.

Following the strategies in the previous studies (Liu et al., 2021a; Ma et al., 2018; Zhu et al., 2021), the ratio of Internet use in the community (excluding the individual him/herself) is applied as a potential instrument. As a valid IV, it is required to be correlated with the endogenous variable

(Internet use). However, it has no significant effect on the dependent variables (environmental outcomes of food consumption). Usually, individuals' Internet use can be influenced by their peers, but the Internet use of their peers has a minimal direct impact on their food consumption. The estimation results are presented in columns (3) and (4) of Table 4.3. Evidence from F-statistics at the first stage further proves that the ratio of Internet use in the community tends to increase the probability of Internet use for each individual. Regarding the effect of Internet use, we can find that our main findings remain, and the magnitudes are almost the same as those presented in Table 4.2. Thus, we can conclude that Internet use has a significantly adverse effect on the environmental outcomes of food consumption, and this finding is consistent when using various methods.

Table 4.3: Robustness tests

	PSM method		**Use another IV**	
	Carbon	**Water**	**Carbon**	**Water**
Internet use	-0.094***	-0.037**	-0.150***	-0.062***
	(0.032)	(0.017)	(0.037)	(0.020)
First stage				
Ratio			0.028***	0.028***
			(0.007)	(0.007)
R-squared	-0.796	-0.791	0.006	0.005
Observations	19973	19973	20105	20105

Notes: *** denotes p < 0.01; ** denotes p < 0.05; * denotes p < 0.1. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses

4.3.3 Heterogeneity analysis

This study explores the heterogeneous effect of Internet use on food environmental footprints across three dimensions: region, age, and income. The sample is divided into an eastern region and a middle and western region. Table 4.4 reveals that Internet use significantly reduces both carbon and water footprints from food consumption in both regions. It is noteworthy that the effect of Internet use is more pronounced in the eastern region, possibly attributed to its more developed network infrastructure, higher network coverage, and faster Internet access. In contrast, the middle and western regions have relatively weaker network infrastructure, with some rural areas lacking high-speed Internet access. Additionally, the eastern region of China is more economically developed, with higher education levels and richer natural resources, further amplifying the impact of Internet use on the environmental footprints of food production in this region.

Table 4.4: Heterogeneity analysis in different regions

	Eastern region		**Middle and western region**	
	Carbon	**Water**	**Carbon**	**Water**
Internet use	-0.197*	-0.170***	-0.160**	-0.068*
	(0.102)	(0.056)	(0.071)	(0.039)
R-squared	0.007	0.005	0.019	0.020
Observations	7210	7210	12895	12895

Notes: *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses.

Age is categorized into three stages: 18–35, 35–60, and over 60 years old. Table 4.5 illustrates the effects of Internet use on these different age groups. Our findings indicate that Internet use does not significantly impact the food carbon or food water footprints of respondents over 60 years old. Meanwhile, Internet use significantly reduces the carbon and water footprints of food for respondents under 60 years of age. Furthermore, the effectiveness coefficient of Internet use in people aged 18–35 years is larger than that in people aged 35–60 years. These results may be attributed to potential differences in food consumption habits among age groups. Young individuals may have a good preference for fresh and healthy food, opting for items that are low in carbon and water consumption. Conversely, older age groups might adhere to more traditional food consumption patterns, showing less concern for environmental factors. Additionally, young people are typically more adept at using the Internet, facilitating their access to diverse information on food consumption and environmental protection, thereby strengthening their environmental awareness and food consumption behavior.

Table 4.5: Heterogeneity analysis at different ages

	Group 1 ($18 \leq$ age < 35)		Group 2 ($35 \leq$ age < 60)		Group 3 ($60 \leq$ age)	
	Carbon	**Water**	**Carbon**	**Water**	**Carbon**	**Water**
Internet use	-0.503**	-0.269**	-0.146**	-0.092**	-0.175	-0.070
	(0.220)	(0.121)	(0.070)	(0.038)	(0.154)	(0.085)
R-squared	0.007	0.000	0.004	0.000	0.018	0.000
Observations	3567	3567	12353	12353	4185	4185

Notes: *** denotes p < 0.01; ** denotes p < 0.05; * denotes p < 0.1. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses.

The results in Table 4.6 indicate that Internet use primarily reduces the carbon and water footprints of food for the high-income group. More specifically, Internet use results in a 27.2% reduction in food carbon footprints and a 12.9% reduction in food water footprints for this group. However, the coefficient of Internet use for low-income groups, though negative, is not statistically significant.

Table 4.6: Heterogeneity analysis at different levels of income

	Low-income group		High-income group	
	Carbon	**Water**	**Carbon**	**Water**
Internet use	-0.081	-0.073	-0.272**	-0.139**
	(0.087)	(0.049)	(0.108)	(0.059)
R-squared	0.003	0.012	0.007	0.011
Observations	9947	9947	10158	10158

Notes: *** denotes p < 0.01; ** denotes p < 0.05; * denotes p < 0.1. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses.

It is plausible that low-income groups experience more pronounced economic pressures and financial constraints, leading them to rely on affordable and convenient food options, which, unfortunately, are often less healthy and have a more significant environmental impact. While the Internet's proliferation may offer more shopping choices for low-income groups, economic considerations might limit their capacity to reduce their environmental impact on food. Furthermore, high-income groups typically have better access to education and information, making them more likely to understand the significance of a healthy diet and how to improve their food environmental footprints. This knowledge empowers them to make healthier and environmentally conscious decisions when purchasing and selecting food. Conversely, low-income groups might lack equivalent access to such knowledge and information, resulting in less significant changes in their food environmental footprints.

4.3.4 Influencing channel

In this section, we analyze the channels through which Internet use influences food carbon and water footprints. We classify foods into two categories: animal-based foods and plant-based foods. Animal-based foods include eggs, pork, poultry, red meat, fish and seafood, and dairy, while plant-based foods consist of fruits, vegetables, tubers, beans, and grains.

Table 4.7: The impact of Internet use on food consumption

	Animal-based food	**Poultry**	**Eggs**	**Pork**
Internet use	-31.233**	8.945**	-24.059**	-14.775***
	(12.774)	(3.648)	(11.006)	(5.319)
R-squared	0.000	0.002	0.001	0.005
Observations	20105	20105	20105	20105
	Plant-based food	**Grain**	**Beans**	**Fruits**
Internet use	2.913	-19.271*	-4.937**	34.516***
	(2.972)	(10.031)	(2.077)	(11.486)
R-squared	0.001	0.002	0.002	0.001
Observations	20105	20105	20105	20105

Notes: *** denotes $p < 0.01$; ** denotes $p < 0.05$; * denotes $p < 0.1$. Year and individual fixed effects are controlled. Robust standard errors are presented in parentheses. We examined the effect of Internet use on each specific food, and here we do not show results that are not statistically significant.

Our findings highlight that Internet use predominantly and significantly reduces the consumption of animal-based foods. More specifically, it reduces the intake of eggs and pork while having a positive effect on poultry consumption. However, the coefficient for plant-based foods is not statistically significant, primarily due to the Internet's role in reducing the consumption of grains and beans but concurrently increasing the intake of fruits. It is noteworthy that Internet use primarily reduces the environmental impact of food by mitigating the consumption of animal-based sources with higher environmental footprints. Given that, in rural China, the consumption of grains and beans often exceeds the recommended dietary guidelines. In contrast, the consumption of fruits tends to fall below the recommended dietary quality intake. We suggest that Internet use not only reduces the environmental footprints of food but also encourages a more rationalized food consumption structure.

4.4 Conclusion

Reducing food carbon and water footprints is a crucial step toward achieving sustainable food consumption. However, the effect of Internet use on these footprints, particularly in rural China, remains poorly understood. In this study, we leverage CHNS data from 2004 to 2011 to examine the causal relationship between Internet use and food carbon and water footprints. Our analysis also explores the pathways through which dietary changes occur. Additionally, we investigate the heterogeneity of Internet use in relation to food environmental footprints across regions, age groups, and income levels. We employ the instrumental variable method to address the endogeneity issue associated with Internet use, and the estimation results from PSM reinforce the robustness of our findings.

The empirical analysis yields three key findings. First, Internet use significantly reduces the food carbon and water footprints of rural residents. Specifically, Internet use reduces the food carbon footprints by 18.1% and the food water footprints by 10.6%. Additionally, education and age are key variables that influence whether consumers use the Internet, while income and age also affect food carbon and water footprints. Second, our results highlight that the Internet promotes the adoption of sustainable food consumption practices, primarily by reducing the consumption of animal-based foods. Finally, we find that Internet use has a more significant impact on lowering food carbon and water footprints for individuals with higher incomes and younger age groups. In comparison, its impact is more limited for those with lower incomes and older individuals.

These findings provide important insights into current discussions on dietary change and environmental sustainability. First, digitization plays a crucial role in influencing sustainable food consumption, with the Internet serving as a platform to promote reductions in the carbon and water footprints associated with food. Additionally, there are significant differences in food carbon and water footprints across income levels and age groups, suggesting that policy interventions should account for factors such as income and age. For example, online education can help younger people develop sustainable food habits, while offline training might be more effective for older adults. Second, Internet use is associated with reduced consumption of eggs and pork and increased consumption of fruits, reflecting its impact on consumer behavior. Governments can leverage the Internet to encourage shifts in dietary patterns, such as promoting reduced animal-based food intake and increased plant-based consumption. Third, we find that Internet use does not significantly influence the food carbon and water footprints of low-income households, likely due to their limited food purchasing options. Given that income is a key factor affecting food carbon and water footprints, raising the incomes of low-income households may be a more effective strategy for advancing sustainable food consumption. Of course, there are some limitations in this study. First, the data used in this study span from 2004 to 2011. While this period includes several years of rapid Internet development in China, future studies could benefit from using more recent panel data. Second, this study focuses on the short-term effects of Internet use on sustainable food consumption, and future research could explore its long-term effects.

Chapter 5: The Effect of the FFCS Project on Sustainable Agricultural Development[9]

5.1 Introduction

With increasing attention being paid to climate change, characterized by global warming, the transition towards carbon neutrality has been placed at the top of the policy agenda in many countries. As a consequence of global warming, incidents such as tropical cyclones are on the rise (Geiger et al., 2021), and the ecological fragility of major rivers and species has been exacerbated (De La Peña et al., 2022; De Lucia & Pazienza, 2019; Thompson et al., 2021). Several laws and bills have been drafted and passed by governments and international organizations to address global warming, including the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Climate Agreement (Thompson et al., 2021). Nevertheless, global emissions of greenhouse gases continue to rise. In 2018, Asia and North America accounted for about 40% of global greenhouse gas emissions (Lamb et al., 2021; Qin & Gong, 2022). According to the Union of Concerned Scientists' 2020 Global CO_2 data, China is one of the highest emitters, accounting for 28% of global greenhouse gas emissions (Hu et al., 2022). To meet global greenhouse gas emission reduction targets and protect the environment, Chinese policymakers have set unprecedented climate ambitions under the new development framework. The ambitious goal, known as "dual carbon", is expected to peak carbon emissions by 2030 and be carbon neutral (or net-zero emissions) by 2060 (Chen & Gong, 2021; Lin & Ge, 2019).

[9] This chapter was published as the following open-access article: Liu J, Ren Y, Hong Y, Glauben T (2023). Does forest farm carbon sink projects affect agricultural development? Evidence from a Quasi-experiment in China. *Journal of Environmental Management*. **https://www.sciencedirect.com/science/article/pii/S0301479723002888**

There are three main ways for China to achieve the “dual carbon” goal. The first approach is to reduce the source intensities of carbon emissions in various energy-intensive industries, including metallurgy, building materials, petrochemicals, chemicals, and electric power (Fisher-Vanden et al., 2004; Lin and Du, 2013). Specific measures include developing non-fossil energy, vigorously augmenting wind, solar, and hydroelectric power, and researching and introducing new technologies. The second is to enhance the ecological carbon sink capacity (Tong et al., 2020; Xu et al., 2016). With a focus on forestry and grasslands, policymakers have promoted large-scale land greening to increase the total amount of forest, grassland, and wetland resources. These measures can enhance ecosystem function, strengthen resource conservation, and increase carbon stocks (Mi et al., 2017; Brouwers et al., 2016). The third way is to establish a carbon emission trading system, whereby enterprises need to purchase carbon emission rights from farmers operating carbon sink forests. This would not only motivate Chinese companies to adopt innovative technologies and processes that meet environmental standards consciously, but also help farmers transform the ecological benefits of the forest into economic benefits (Gao et al., 2020; Hu et al., 2020; Liu et al., 2013).

Importantly, the implementation of carbon emission trading has been increasingly discussed worldwide. The National Development and Reform Commission of China (NDRC) also launched the pilot work of carbon emission trading in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen in 2011 (Hong et al., 2022). Forests function as carbon sinks and are expected to be an effective way to manage carbon dioxide emissions. However, like the regulations on carbon trading in developed countries in Europe and the United States, not all forests and forestlands in China are available to sell carbon emission rights (Sun et al., 2016). Only after a project is approved and accepted by relevant organizations and obtains relevant certificates (Wei

& Xiao, 2022; Zhou et al., 2019) can the project initiator sell the carbon emission rights. Generally, the forest projects that can sell carbon emission rights are uniformly FFCS projects. There are three main categories of FFCS projects in China: voluntary carbon standard (VCS), clean development mechanism (CDM), and China certified emission reduction (CCER). The VCS and CDM are designed and managed by Verra (called Certified Carbon Standards by 2018) and the Clean Development Mechanism Executive Board, respectively. The CCER is designed and managed by the NDRC.

FFCS projects aim to mitigate global warming and enhance environmental and ecological benefits by expanding forest areas to absorb carbon dioxide and implementing a carbon emission trading system to incentivize enterprises to reduce their carbon emissions. On the one hand, FFCS projects contribute to improving air quality (Baumgardner et al., 2012; Smith et al., 2013), promoting off-farm employment of agricultural labor and increasing farmers' income (Aggarwal & Brockington, 2020; Boyd et al., 2007), which is conducive to agricultural TFP growth (Diao et al., 2018; Sheng et al., 2020). However, China has about 18% of the world's population but only 5.51% of the world's forest area, 3.34% of the world's forest stock, and 22.96% of the forest cover (Zhang et al., 2022). The development of FFCS has also raised concerns about China's food security and agricultural development. First of all, due to the lack of incentives and supervision in the implementation of FFCS projects, some high-quality flat farmland may also be used for carbon sequestration, leading to a decrease in food production (Hu et al., 2021), which will hurt sustainable agricultural development. Moreover, the FFCS projects prohibit the cultivation of cash crops such as mushrooms and herbs in the forest, which may affect some cash crop yields (Rao et al., 2019). Although the existing literature has extensively discussed the impact of FFCS on the allocation of agricultural factors, such as land, labor, employment structure, and income structure, there is a lack of knowledge about whether FFCS projects can influence agricultural development.

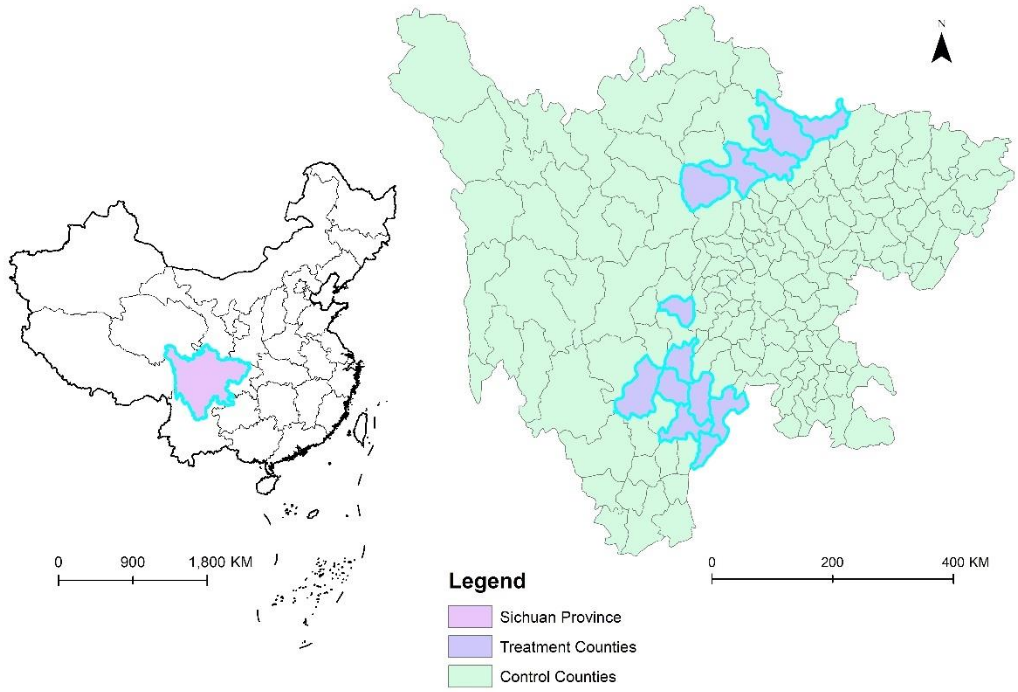


Figure 5.1: Sample distribution status. Source: Authors' own calculation based on the collected data

The purpose of this study is to explore the potential effect of the FFCS project on agricultural sustainable development by using agricultural TFP as a comprehensive index to measure agricultural sustainable development (Cao & Birchenall, 2013; Gong, 2018). Specifically, based on the panel data of 140 counties in Sichuan province from 2002 to 2018, this study uses the PSM-DID method to examine the causal effect of FFCS projects on agricultural TFP and sheds light on their dynamic effect and underlying mechanisms. The distribution of FFCS projects in Sichuan is shown in Figure 5.1. The counties with FFCS projects are treatment counties, while those without

FFCS projects are control counties. Sichuan is selected for two main reasons. Firstly, the province is rich in forest land resources, with a climate and soil conditions that are particularly suitable for tree growth, making it an important natural carbon reservoir in China and the world. It is also one of the pilot provinces for FFCS projects in China and a priority area for the development of the forest carbon sink industry in China. All three categories of FFCS projects are present in Sichuan province, with one CCER project, one VCS project, and two CDM projects, covering a total of 13 counties and a population of about 2.72 million. The second reason for choosing Sichuan province is that it has more complete statistical data than any of the other provinces. For instance, this study examines the role of human health as a key channel variable in explaining the impact of FFCS projects on agricultural TFP. However, most provinces in China only report medical expenditures and visits at the provincial or municipal level, and only Sichuan province has comprehensive county-level healthcare data since 2000.

The development of agriculture mainly comes from the increase in factor input and agricultural TFP. Since the agricultural growth brought by input factors is limited, increasing agricultural TFP is an important way to achieve agricultural development.

As shown in Figure 5.2, the agricultural TFP changes mainly come from changes in output and input factors, such as labor and capital, as well as external factors, such as industrial structure. In the process of agricultural production, the labor force is usually represented by the number of agricultural laborers, while capital includes specific agricultural factor inputs such as land, fertilizer, and machinery (Kuang et al., 2022; Zhang et al., 2015). The growth of agricultural TFP can also improve the output of the whole agricultural sector, optimize the structure of input factors, and promote the development of the agricultural sector. At the same time, it releases a large number of surplus rural labor and promotes industrial and service development and economic restructuring

(Lin & Ge, 2019). The green part at the bottom of Figure 5.2 illustrates the relationship between agricultural TFP and input factors and industry structure.

The FFCS projects can affect agricultural TFP growth in three ways: health, income, and industry structure, but the results are not precise. First, FFCS projects certainly increase the area of local forests. Forests are expected to absorb harmful particulate matter from the air, reduce local PM2.5 values, and improve the health of the labor force. Health status is an important human capital, and better health status means higher labor quality and agricultural TFP (Cole & Neumayer, 2006； Dong et al., 2021). However, the rapid development of urbanization may also deteriorate air quality, and the influx of the rural labor force into cities may also increase the burden on the urban environment.

Second, FFCS projects need to occupy most of the forest land and prohibit other related forestry production activities, which will promote the local labor force from the primary industry to the secondary and tertiary industries. Industrial structure directly affects the ratio of production factors such as labor and capital in the agricultural sector, thus affecting agricultural TFP (Sun et al., 2016; Chen & Gong, 2021). It is important to note that China is undergoing rapid urbanization, with the urbanization rate rising rapidly from 36.2% in 2000 to 63.9% in 2021. As a result, a large number of surplus rural laborers have entered the secondary and tertiary industries, meeting the needs of China’s industrial upgrading (Chari et al., 2021). However, it is challenging for energy-intensive enterprises to complete the transformation within a short timeframe, and purchasing carbon emission rights will further increase their production costs, potentially hindering China's industrialization process.

Last, afforestation activities in FFCS projects require labor, and to reduce costs, project owners often recruit labor from villages surrounding the project area. This has created new jobs for local residents and boosted the incomes of farming families. After the completion of carbon emissions trading, the revenue from the sale of the carbon sink will be distributed according to the land area of the farmers participating in the project. However, FFCS projects do not allow farmers to continue to operate or lease the land in the project area, which may reduce the grazing income and land rental income of farmers (Kallio et al., 2018; Smith & Scherr, 2003). Changes in income will directly affect agricultural input factors such as labor, fertilizer, and machinery (Liu et al., 2019), which in turn affect agricultural TFP. Considering the above three aspects, whether FFCS projects indeed have an effect on TFP is unclear; thus, it is necessary to explore the causal relationship between the FFCS projects and agricultural TFP.

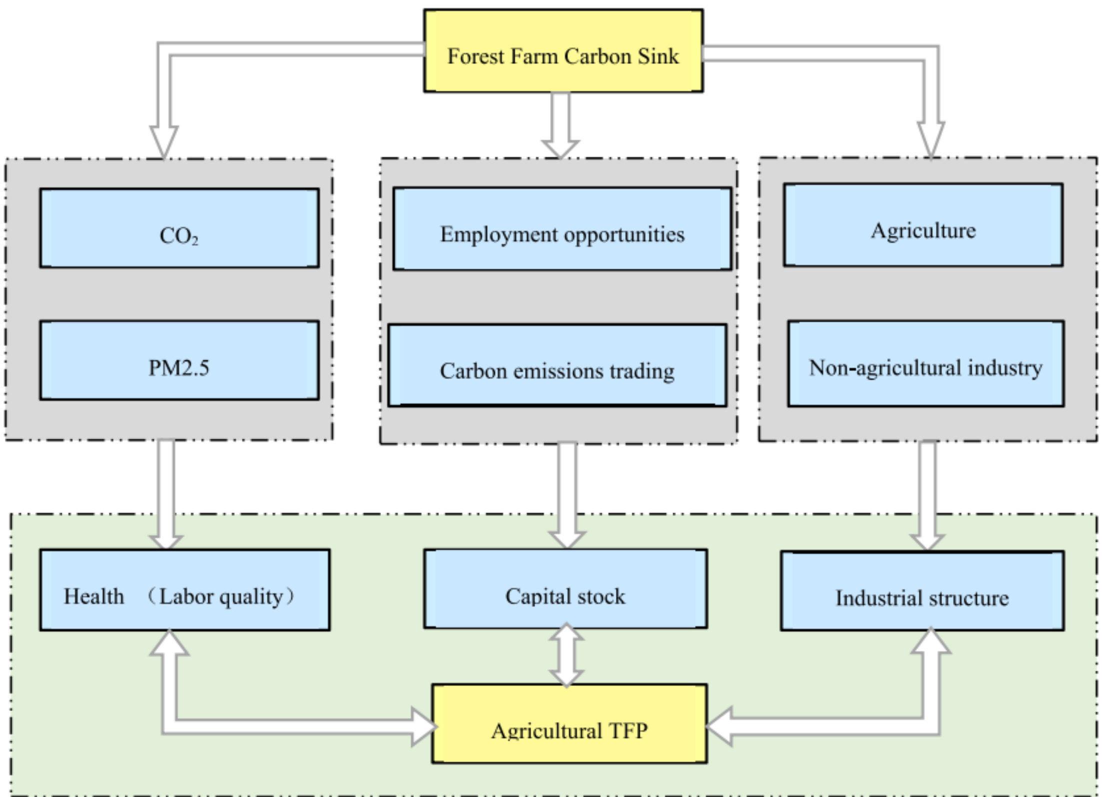


Figure 5.2: Conceptual framework.

5.2 Method and Data

5.2.1 Method

Following Li and Zhang (2013) and Liu et al. (2019), this study formulated the agricultural production function as Eq. (5-1). Where Y_{it} denotes agricultural output production in year t for the *i-th* county. $Labor_{it}$, $land_{it}$, Fer_{it}, and $Mach_{it}$ represent the labor, land, fertilizer and machinery inputs, respectively. α, β, γ and τ are the parameters to be estimated. A is the agricultural TFP.

$$Y_{it} = A_{it}Labor_{it}^{\alpha}Land_{it}^{\beta}Fer_{it}^{\gamma}Mach_{it}^{\tau} \tag{5-1}$$

To estimate the agriculture TFP, the Cobb-Douglas function in log-linear form is adopted as shown in Eq. (2).

$$LnTFP_{it} = LnY_{it} - \alpha LnLabor_{it} - \beta Lnland_{it} - \gamma LnFer_{it} - \tau LnMach_{it} + e_{it} \tag{5-2}$$

Where e_{it} is the random error term and the others are logarithmic variables. Based on Eq. (5-2), this study used a fixed-effects model to control for individual effects across counties and time effects across years and then estimated the agricultural TFP of counties.

However, various input factors and outputs can be observed in the agricultural production process, and agricultural TFP can also be estimated. Therefore, Eq. (5-2) may have an endogeneity problem caused by two-way causality. In other words, the agricultural TFP of the latter year may also be affected by the agricultural TFP of the previous year. To correct the estimation bias, this study extended the dynamic panel data model based on Eq. (5-2), and the model is shown in Eq. (5-3).

$$LnTFP_{it} = LnTFP_{it-1} + LnY_{it} - \alpha LnLabor_{it} - \beta Lnland_{it} - \gamma LnFer_{it} - \tau LnMach_{it} + e_{it} \tag{5-3}$$

Arellano and Bond (1991), as well as Arellano (1995), proposed the generalized method of moments (GMM) to solve the endogeneity problem by introducing the endogenous variable lag term as an instrumental variable. Based on Eq. (5-3), a more accurate agricultural TFP of each county can be obtained by using the GMM estimation.

FFCS projects have been implemented only in 13 counties, and the differences between counties in Sichuan are minor, which is consistent with the analysis conditions of the natural experiment. Hence, in this study, counties with FFCS projects were considered as the treatment group and counties without FFCS projects were considered as the control group. The difference-in-difference specification was used to assess the relationship between the FFCS projects and agricultural TFP (Chen et al., 2021; Pan et al., 2022), based on the following regression set-up Eq. (5-4):

$$Y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 C_{it} + \beta_3 T_{it} + \gamma Z_{ii} + e_{it} \tag{5-4}$$

In Eq. (4), Y_{it} represents the agricultural TFP of the *i-th* county in year *t.* The variable of interest is D_{it}, a dummy variable that equals 1 in the years after county i implemented FFCS projects and zero otherwise. The coefficient β_1 therefore indicates the effect of FFCS projects on agricultural TFP. C_{it} and T_{it} are vectors of county and year dummy variables that account for the fixed effects of county and year. Z_{ii} represents a range of other socio-economic control variables including GDP, Area, Fixed, Finance, Industrial, Sickbed, Irrigation, Urbanization etc., and e_{it} is the random error term.To investigate the dynamics of the relationship between FFCS projects and agricultural TFP, this study follows Beck et al. (2010), including a series of dummy variables in the standard regression to trace the year-by-year effects of FFCS projects on agricultural TFP.

$$Y_{it} = \beta_0 + \beta_1 D_{it}^{-10} + \beta_2 D_{it}^{-9} + \cdots + \beta_3 D_{it}^{9} + \beta_{20} D_{it}^{10} + \beta_{21} C_{it} + \beta_{22} T_{it} + \gamma Z_i + \varepsilon_{it} \tag{5-5}$$

Where the dummy variables of FFCS projects, are equal to zero, except as follows: D_{it}^{-j} is equal to 1 for the county in the *j-th* year before implementation, while D_{it}^{+j} equals 1 for the county in the *j-th* year after implementation. The year of implementation is excluded; therefore, we estimate the dynamic effect of FFCS projects on the agricultural TFP relative to the year of implementation. Other variables are the same as in Eq. (5-4).

Another purpose of this study is to understand the channels through which FFCS projects affect agricultural TFP. In Eq. (5-6), M_{it} represent the channel variables including health, savings and industrial structure. Health and savings can also be regarded as the proxy variables of labor and capital, and the proportion of the first, second and third industries in GDP as the proxy variables of industrial structure. The effect of FFCS projects on channel variables was estimated based on Eq. 6, and this study mainly focuses on the effect of FFCS projects on health.

$$M_{it} = \beta_0 + \beta_1 D_i + \beta_2 C_i + \beta_3 T_t + \gamma Z_i + e_{it} \tag{5-6}$$

It should be noted that the selection of the FFCS project counties may not be random. In other words, counties with abundant natural forest resources are more likely to be selected for forest carbon sequestration projects. In this case, sample selection bias may exist in the treatment group samples, which could lead to the endogeneity problem in the estimation. Therefore, this study first adopted the PSM method to match the treatment group with a similar control group. After correcting the sample selection bias, the DID method was used to estimate the effect of FFCS projects on agricultural TFP.

5.2.2 Data

There are four groups of variables in this study: (1) agricultural TFP, input and output variables, (2) FFCS projects, (3) channel variables, and (4) control variables. The details of the variables in this study are shown in Table 5.1.

Agricultural TFP, the variables of interest, are calculated based on fixed-effects estimation and a generalized method of moments estimation. Agricultural TFP is calculated based on agricultural input-output factors in each county. Among the output and input variables of production, labor, land, fertilizer, and machinery, only production is measured in Chinese Yuan (CNY) value. Due to the difference in price levels among counties, this study uses the price index of each county to adjust the agricultural GDP before estimating the agricultural TFP.

The primary variable of this study is the implementation of FFCS projects. The dummy variable D equals one when the county has implemented an FFCS project; otherwise, D equals zero. Note that the two CDM projects in this study started in 2006 and 2010, respectively. The CCER projects and VCS projects both started in 2011. Therefore, to test the possible heterogeneity among CDM, VCS, and CCER projects, one robustness test in this study was to exclude the CCER projects and keep only two international projects, CDM and VCS, and to reestimate the effect of FFCS projects on agricultural TFP.

There are five channels considered in this study, including health, savings, and the proportion of primary, secondary, and tertiary industries in GDP. The average number of hospital visits per person was used to measure health at the county level, which means that the higher the value of the health variable, the worse the health of the county. Savings are an important proxy variable for income, and the growth in savings may contribute to an increase in agricultural TFP. Changes in industrial structure may also affect the change in agricultural TFP, but the results are mixed.

The control variables include three categories. The first category is related to economic development, including GDP, fixed investment level, financial level, and urbanization level. The second category is related to natural conditions, including the county area and irrigable area. Finally, the number of hospital sickbeds is used as a proxy variable to control the level of medical facilities at the county level. Regarding the sources of variables, the data on health and sickbed variables are sourced from the Sichuan Health Statistical Yearbook (Health Commission of Sichuan Province). The data for FFCS projects primarily come from the official websites of the three forest carbon sink projects, along with their plans.[10]. Others are from the Sichuan Statistical Yearbook (Sichuan Province Bureau of Statistics).

[10] All detailed information about the projects can be downloaded here, CDM: https://cdm.unfccc.int/Projects/projsearch.html; VCS: https://registry.verra.org/app/search/VCS/All%20Projects; CCER: http://cdm.ccchina.org.cn/zyblist.aspx?clmId=164, access on 12, December. 2021.

Table 5.1: Variable definitions and descriptive statistics

Variables	Definition	Control	Treatment	Diff [a]
		(2)	(3)	(3) − (2)
TFP_{FE}	Agricultural TFP (fixed-effects estimates) [b]	2.102 (0.096)	2.068 (0.082)	−0.034***
TFP_{GMM}	Agricultural TFP (Generalized method of moments estimation) [b]	2.194 (0.081)	2.171 (0.072)	−0.023***
Health	Average number of hospital visits per person	2.030 (2.228)	1.671 (3.059)	−0.359**
Saving	Resident savings (million CNY) [b]	9.049 (0.986)	8.600 (1.048)	−0.449***
First	The proportion of the primary industry in GDP	0.269 (0.127)	0.296 (0.136)	0.027***
Second	The proportion of the secondary industry in GDP	0.432 (0.180)	0.443 (0.172)	0.011
Third	The proportion of the tertiary industry in GDP	0.299 (0.136)	0.261 (0.103)	−0.038***
GDP	Gross domestic product per capita (million CNY) [b]	4.814 (0.854)	4.527 (0.799)	−0.287***
Area	County area (ha) [b]	12.289 (0.899)	12.591 (0.368)	0.302***
Fixed	Investment in fixed assets (million CNY) [b]	7.891 (1.492)	7.289 (1.099)	−0.602***
Finance	Loans of financial institutions (million CNY) [b]	7.476 (1.613)	6.665 (1.145)	−0.811***
Industrial	Industrial value above designated size (million CNY) [b]	7.408 (2.695)	6.585 (1.582)	−0.823***
Sickbed	Number of hospital beds (thousand) [b]	9.048 (1.132)	8.511 (0.583)	−0.537***
Irrigation	Effective irrigated area (ha) [b]	8.976 (1.605)	8.175 (0.859)	−0.801***
Urbanization	Urbanization rate	0.258 (0.158)	0.198 (0.125)	−0.060***
Production	The total output value of Agriculture (million CNY) [b]	7.144 (1.293)	6.683 (0.815)	−0.461***
Labor	Number of employees in the primary industry (thousand numbers) [b]	4.520 (0.943)	4.297 (0.577)	−0.222***
Land	Actual arable land area (ha) [b]	9.811 (1.079)	9.568 (0.689)	−0.244***
Fertilizer	Fertilizer use (tons) [b]	8.432 (2.255)	8.373 (0.835)	−0.059
Machinery	Total power of agricultural machinery (thousand kilowatts) [b]	4.869 (1.031)	4.204 (0.704)	−0.666***
Observations		2159	221	

Notes: The mean values are presented, and the standard deviations are within parentheses; *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$. [a] T-test was applied. [b] Natural logarithm value.

5.3. Results and discussion

5.3.1 Estimation results for the Cobb–Douglas production function

In this study, Cobb–Douglas production functions are used to estimate agricultural TFP. Compared with the translog production function, the Cobb–Douglas function is more concise and intuitive, and all parameters have obvious economic interpretation (Liu et al., 2019). As shown in Table A5.1, both fixed-effect and GMM estimation results showed that fertilizer and machinery had a positive relationship with agricultural productivity, which was consistent with the results of Justin (1992) and Liu et al. (2019). Specifically, each 1% increase in machinery input will increase the total agricultural output by about 0.174% to 0.260%, suggesting that mechanization is still the main driving force for China's agricultural development. Each 1% increase in the input of chemical fertilizer will increase the total agricultural output by 0.155% to 0.171%, suggesting that chemical fertilizer is also an important factor to promote China's agricultural production, and the extensive agricultural development mode characterized by high pesticide and fertilizer inputs is still the main form of agricultural production in China. After the implementation of FFCS projects (2006 to 2018), we observed significant changes in the mean values of $\mathrm{TFP}_{\mathrm{FE}}$ and $\mathrm{TFP}_{\mathrm{GMM}}$ in the control and treated counties (shown in Figure 5.3).

This study conducted a parallel trend test between the treatment group and the control group, and the results showed that the agricultural TFP growth trend before the FFCS project implementation met the parallel trend assumption, as shown in Fig. A5.1. The results of the average treatment effects of the DID approach are displayed in Table 5.2, which includes the results of six regressions with agricultural TFP as the dependent variable. Columns 1 and 2 show the effect of FFCS projects on agricultural TFP without control variables. After adding a set of full control variables, the estimation results of DID are shown in Columns 3 and 4. It is important to note that none of the results in the first four columns consider endogeneity of FFCS projects caused by sample selection bias. Finally, after correcting for sample selection bias using the PSM-DID method, the estimated impact of FFCS projects on agricultural TFP is shown in Columns 5 and 6. The PSM validity test and the common support area of PSM are displayed in Table A5.2 and Figure A5.2, respectively.

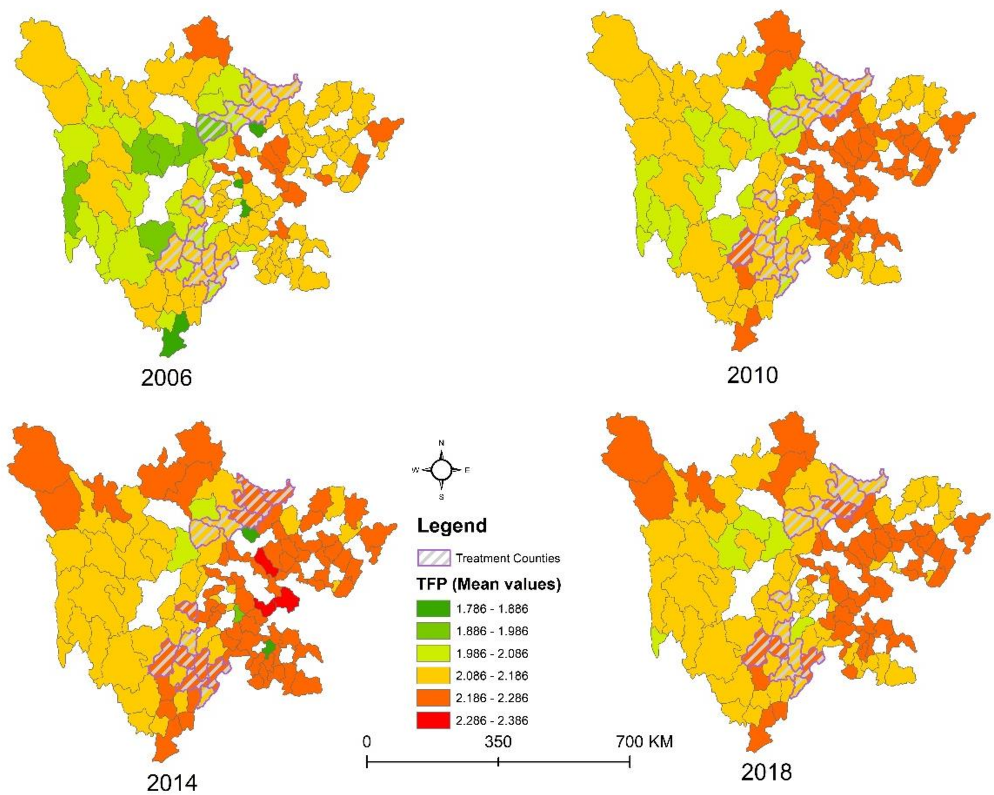


Figure 5.3: Spatial and temporal variation of TFP means at the county level

Note: The white colour indicates the counties with missing data.

5.3.2 The average treatment effect of FFCS projects on agricultural development

As shown in Table 5.2, all regression results indicate that the FFCS projects significantly increased agricultural TFP. Specifically, the FFCS projects increased agricultural TFP by 1.7% to 2.4%. In Columns 5 and 6, the regression coefficients of FFCS are 0.022 and 0.024, respectively, which are both larger than the regression coefficients of FFCS without considering endogenous selection bias (Columns 1 to 4). This result indicates that if the sample selection bias is not considered, the effect of FFCS on agricultural TFP will be underestimated. This study also found that the coefficient of county fixed asset investment is significantly negative. One explanation may be the unequal distribution of fixed assets in China between urban and rural areas. (Smith et al., 2013; Tan et al., 2005). In China, a significant portion of fixed asset investment is concentrated in urban areas, particularly the real estate sector. This results in a substantial amount of agricultural land being occupied by cities and leads to pollution of the rural environment. (Lu et al., 2019). Data from China's National Bureau of Statistics show that China's urban area was 30,406.19 km^2 in 2004 and 62,420.53 km^2 in 2021, an increase of about 105.289% in 17 years. As a result, the effect of fixed asset investment on agricultural TFP may be negative in the short term. However, in the long term, with the increasing proportion of fixed asset investment in rural areas, fixed asset investment may have a positive effect on agricultural TFP. (Li and Qi, 2011). Besides, this study also shows that counties with better financial conditions have higher agricultural TFP, which can be explained by the fact that convenient finance can promote private investment in agricultural production, thus having a positive impact on agricultural TFP (Dong et al., 2022). As shown in Table 5.2, the coefficient of sickbed is not significant, which may be because the positive effects of medical service facilities take longer to emerge. Besides, the construction of a large number of medical facilities may lead to a decrease in agricultural fixed investment (Li & Qi, 2011; Lu et al., 2019). Therefore, it may hurt agricultural TFP in the short term. However, in the long term, medical service facilities contribute to human capital growth and thus may have a positive effect on agricultural TFP (Dong et al., 2022).

Table 5.2: Effects of forest carbon sink on agricultural TFP.

Variables	DID				PSM-DID (Kernel)	
	TFP_{FE}	TFP_{GMM}	TFP_{FE}	TFP_{GMM}	TFP_{FE}	TFP_{GMM}
	(1)	(2)	(3)	(4)	(5)	(6)
D	0.017**	0.021**	0.017**	0.020**	0.022***	0.024***
	(2.389)	(2.575)	(2.271)	(2.520)	(2.807)	(3.142)
GDP			0.005	0.024	0.006	0.004
			(0.630)	(0.363)	(0.513)	(0.322)
Area			−0.002	0.160	−0.017	−0.026
			(−0.051)	(0.762)	(−0.057)	(−0.077)
Fixed			−0.007*	−0.057*	−0.007*	−0.007*
			(−1.739)	(-1.729)	(−1.675)	(−1.676)
Finance			0.007	0.057*	0.005	0.006
			(1.584)	(1.687)	(0.857)	(0.887)
Industrial			−0.000	0.002	0.000	0.000
			(−0.189)	(0.130)	(0.003)	(0.094)
Sickbed			−0.002	−0.027	−0.010	−0.017**
			(−0.294)	(−0.551)	(−1.585)	(−2.338)
Irrigation			−0.000	0.008	−0.000	0.001
			(−0.083)	(0.450)	(−0.225)	(0.641)
Urbanization			−0.007	−0.154	−0.011	−0.031
			(−0.309)	(−0.747)	(−0.490)	(−1.257)
Constant	2.192***	2.098***	2.184***	6.864***	2.380	2.402
	(6051.216)	(5125.325)	(7.689)	(3.420)	(1.018)	(0.929)
Observations	2380	2380	2380	2380	1664	1664
R-squared	0.663	0.702	0.663	0.754	0.670	0.721

Note: Fixed-effects models were used to control for time and individual effects. Standard errors are cluster-corrected at the county level. *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$.

5.3.3 Robustness check

To examine the robustness of our estimation results, two strategies were applied in this study. First, the counties where CCER projects had been implemented were removed, and the treatment group was redefined as the group of counties where the two CDM and VCS international projects had been implemented. This study then reassessed the effect of the FFCS projects on agricultural TFP by using the DID method, and the results are shown in the first two columns of Table 5.3. The results displayed in Table 5.3 show that the FFCS projects significantly improved agricultural TFP. However, the coefficient representing the effect of the project is about twice as large as that in Table 5.2. One possible explanation is that FFCS international projects have a greater effect on agricultural TFP than FFCS domestic projects. In other words, the benefits of international projects are more pronounced than those of domestic projects. International projects were started earlier than domestic projects, which may be the main reason why the average effect of international projects is larger than that of domestic projects. In addition, the variation can also be traced to differences in site selection, implementation methods, and execution standards of different projects.

Table 5.3: Robustness tests.

	DID (Delete CCER projects)		PSM-DID (Neighbour)		PSM-DID (Radius)	
Variables	TFP_{FE}	TFP_{W}	TFP_{FE}	TFP_{W}	TFP_{FE}	TFP_{W}
D	0.046***	0.049***	0.022***	0.024***	0.020***	0.022***
	(3.412)	(4.338)	(4.736)	(4.752)	(4.902)	(4.944)
GDP	0.002	0.002	0.006	0.005	0.004	0.003
	(0.217)	(0.215)	(0.725)	(0.463)	(0.616)	(0.352)
Area	−0.004	0.020	−0.009	−0.018	−0.005	−0.012
	(−0.136)	(0.720)	(−0.047)	(−0.084)	(−0.028)	(−0.061)
Fixed	−0.006	−0.007	−0.007**	−0.007**	−0.006*	−0.007*
	(−1.367)	(−1.459)	(−2.062)	(−2.110)	(−1.918)	(−1.899)
Finance	0.008*	0.010**	0.006	0.007	0.007	0.008
	(1.803)	(2.040)	(1.159)	(1.194)	(1.436)	(1.472)
Industrial	−0.001	−0.001	−0.000	0.000	0.000	0.001
	(−0.257)	(−0.402)	(−0.021)	(0.129)	(0.153)	(0.284)
Sickbed	−0.002	−0.009	−0.010**	−0.017***	−0.010*	−0.017***
	(−0.317)	(−1.269)	(−2.021)	(−3.086)	(−1.945)	(−3.010)
Irrigation	0.000	0.002	−0.000	0.001	−0.001	0.001
	(0.014)	(0.693)	(−0.288)	(0.954)	(−0.437)	(0.797)
Urbanization	−0.010	−0.029	−0.011	−0.031	−0.004	−0.021
	(−0.384)	(−1.047)	(−0.577)	(−1.545)	(−0.206)	(−1.111)
Constant	2.212***	1.968***	2.307	2.333	2.270	2.275
	(7.731)	(7.222)	(1.541)	(1.425)	(1.619)	(1.484)
Observations	2193	2193	1677	1677	1820	1820
R-squared	0.6611	0.7014	0.6696	0.7214	0.6740	0.7242

Note: Fixed-effects models were used to control for time and individual effects. Standard errors are cluster-corrected at the county level. *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$.

The second approach to assessing robustness in this study involves re-matching the treatment and control group samples using various matching methods. Nearest neighbour matching and radius matching methods. The DID method was then used again to estimate the effect of FFCS projects on agricultural TFP. Results are shown in Columns 3 to 6 of Table 5.3. The results showed that regardless of whether neighbour matching or radius matching was used, there was a positive relationship between FFCS projects and agricultural TFP. Through nearest neighbour matching, DID results showed that FFCS projects increased agricultural TFP by about 2.2% to 2.4%, while radius matching showed that FFCS projects increased agricultural TFP by about 2.0% to 2.2%. Compared with the results of kernel matching in Table 5.2, the results obtained by the three different matching methods are largely consistent; that is, compared with the control group, the counties with FFCS projects increased their agricultural TFP by 2.0% to 2.4%.

5.3.4 Dynamic effects of FFCS projects on agricultural development

The dynamic effects of FFCS projects on agricultural sustainable development are displayed in Figure 5.4(a) and Figure 5.4(b). The vertical axis of the two figures represented the agricultural TFP estimated by FE and GMM, respectively. The horizontal axis represents the year in which the FFCS projects started, +*j* represents the *j-th* year after project implementation and -*j* represents the *j-th* year before project implementation. The year in which the planting of the trees started according to the project plan is used as the first year of the project start and as a reference year for the other years.

As shown in Figure 5.4, there was no significant change in agricultural TFP between the years prior to the project, and this was also the case in the first year of implementation. The impact of agricultural TFP can be observed in the second year of project implementation, that is the FFCS projects significantly improved agricultural TFP after two years of implementation. It is important to note that there is still a significant increase in agricultural TFP in the years following the second year of project implementation, but the growth trend remains largely at the same level, suggesting that the effect of FFCS on agricultural TFP is likely to be one-off rather than sustained in the medium term. This is similar to the result obtained by Justin (1992) on the impact of China's household responsibility system (HRS) on agricultural TFP. He explained that the HRS has increased China's agricultural TFP by 37% but it is likely a one-off and not a sustainable effect. In this study, there are two possible reasons for the lack of sustained effects of the FFCS projects on agricultural TFP. Firstly, the project could improve the environment and benefit the health of the local people, but the healthy impact on agricultural TFP may take longer to show up significantly. Second, China's carbon sink trading market is still being developed and not yet complete. In other words, FFCS projects cannot play a major role in the short term by selling carbon emission rights and converting ecological benefits into economic benefits. Therefore, it seems that FFCS projects have only a short-term impact on agricultural TFP and no sustainable effect in the medium term; also, the long-term effect is uncertain at present.

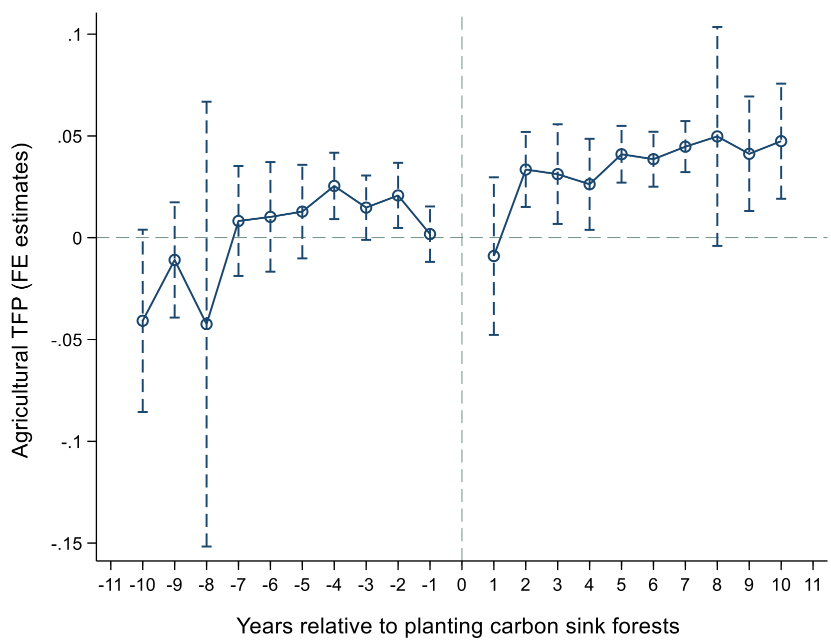


Figure 5.4(a): Dynamic effects of forest carbon sink (fixed-effects estimates)

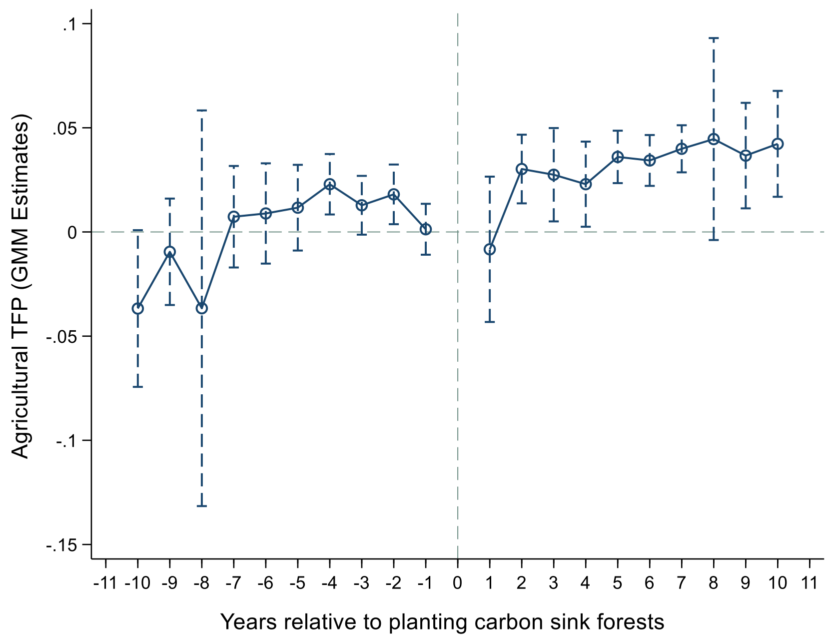


Figure 5.4(b): Dynamic effects of forest carbon sink (GMM estimates)

5.3.5 Mechanisms

As aforementioned, FFCS affects agricultural TFP through three potential mechanisms: health, savings, and industrial structure. The specific results are shown in Table 5.4. The first two columns show the effect of FFCS projects on health and savings. The last three columns show the effect of FFCS projects on industrial structure, specifically on the proportion of primary, secondary and tertiary industries in GDP. The estimated coefficient of FFCS on health is −0.382, with significance at 1% level, which does not mean that the implementation of FFCS is detrimental to people's health. On the contrary, in this study, the annual number of medical visits per capita was used to measure the health level of residents; hence, the interpretation of this coefficient should be that the annual number of medical visits per capita in the county decreased by 0.28 after the implementation of the FFCS projects. In other words, the implementation of the FFCS project is beneficial to the health level of residents. Plants in carbon sinks can absorb harmful substances such as sulfur dioxide and hydrogen fluoride, improving local air quality and positively affecting people's health. At the same time, health is an important human capital, and the improvement of health is beneficial to the quality of the labor force, which results in a positive effect on agricultural TFP.

The coefficient of FFCS projects on savings is 0.120 and is significant at the 95% level, which indicates that FFCS projects have a significant positive effect on residents' savings. The construction and maintenance of carbon sink forests can provide new employment opportunities to residents, which can help increase their income. Moreover, residents can sell part of their carbon emission rights to enterprises in the carbon sink trading market, thus gaining part of their income. The increase in income can reduce their budget constraints to purchase agricultural input factors, increase residents' savings, and thus increase agricultural TFP.

The results show that the coefficient of FFCS projects on the proportion of primary industry in GDP is significantly negative, and the coefficient of the proportion of tertiary industry in GDP is significantly positive. However, we do not find a significant coefficient of the proportion of the tertiary industry in GDP. Specifically, the development of FFCS projects reduced the proportion of primary industry in GDP by 3.7%, while the proportion of tertiary industry in GDP increased by 4.9%. This suggests that FFCS projects can facilitate the upgrading of local industrial structures, thereby promoting the growth of TFP in agriculture. In fact, although a large number of the rural labor force have migrated to urban areas since China's reform and opening up, there is still a large amount of surplus labor force in rural China. The implementation of FFCS projects promoted the local surplus agricultural labor force to engage in secondary and tertiary industrial production activities, thus optimizing the industrial structure and improving agricultural TFP.

Table 5.4: The effect of the FFCS project on health, savings, and industrial structure.

	Health	Saving	First	Second	Third
D	−0.382***	0.120**	−0.037**	−0.012	0.049**
	(−3.218)	(1.978)	(−2.091)	(−0.477)	(2.149)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	2380	2380	2380	2380	2380
R-squared	0.810	0.977	0.930	0.816	0.682

Notes: The mean values are presented, and the standard deviations are within parentheses. Standard errors are cluster-corrected at the county level. *** is $p < 0.01$; ** is $p < 0.05$; * is $p < 0.1$.

5.4 Conclusion

FFCS Projects can be an effective measure for China to achieve carbon neutrality and mitigate global warming. However, little is known about the unintended effects of FFCS projects on agricultural development. In this study, agricultural TFP is proxied as the comprehensive index of agricultural development. We constructed a theoretical analysis framework to examine the effect of FFCS projects on agricultural development and empirically investigated the relationship between them. The PSM-DID method was adopted to alleviate the influence of endogeneity problems caused by sample selection bias in the empirical results. In addition, the channels through which FFCS projects influence agricultural TFP were also discussed in this study. In order to mitigate the adverse effects of human activities on climate change, several transitional economies, such as India, Vietnam, and Brazil, have also implemented FFCS projects (Boyd et al., 2007; Hu et al., 2021), while no specific studies have been conducted to reveal the unintended effects of FFCS projects. As these countries, such as China, undergo significant economic transitions and face substantial environmental challenges, the positive impact of FFCS projects on agricultural TFP in China offers a valuable experience. This can motivate their projects by considering the unique aspects of FFCS projects in each country.

The results of this study lead to the following main conclusions. First, FFCS projects have a significant positive effect on agricultural development. Specifically, FFCS increased agricultural TFP by 1.7% to 2.4%, and the effect of FFCS on agricultural TFP would be underestimated if the endogeneity due to sample selection bias was not taken into account. Second, health, savings and industrial structure are the important channels through which FFCS projects affect agricultural TFP. Specifically, FFCS projects not only benefit health and savings but also promote the optimization of the industrial structure, thus having a positive effect on agricultural TFP. Like HRS, the effect of FFCS projects on agricultural TFP is likely to be one-off rather than sustainable. Third, there is heterogeneity among different FFCS projects. The positive effect of international projects (CDM and VCS), on agricultural TFP is greater than that of national projects (CCER).

This study has the following important policy implications. First, the implementation of FFCS projects not only absorbs carbon dioxide to mitigate global warming but also contributes to agricultural TFP growth. Policymakers can implement FFCS projects in more counties to contribute to China's carbon neutrality goal, improve agricultural TFP, and promote economic development. Second, consider that FFCS projects also affect labor health, income, and industrial structure. Policymakers may consider implementing FFCS projects in areas with poor human health, lower income, and an unbalanced industrial structure. This allows FFCS projects to benefit the local ecology and contribute to improving residents' health, income, and industrial structure. By doing so, the unintended effect of FFCS projects could also facilitate agricultural development in the targeted regions. Finally, international projects have a greater effect on agricultural TFP than domestic projects because of their longer implementation duration. Therefore, policymakers may consider how to maintain the effective practice of FFCS projects in the long term. In addition, the implementation and regulations of domestic projects can also learn more from the experience of international projects, thus improving the quality of FFCS projects.

The limitations of this study are as follows. First, the study is limited by the availability of data. Although this study accurately estimated the impact of FFCS projects on agricultural TFP based on panel data of 140 counties from 2002 to 2018, the data were limited to one province as a case study. Future research may consider collecting more data from other provinces where FFCS projects have also been implemented, which can improve the national representativeness of estimation results. Second, this study only focuses on the overall impact of FFCS projects on agricultural TFP. Subsequent studies may consider decomposing TFP in terms of scale effect, technical efficiency, and technological progress, and explore their relationships with FFCS projects.

Chapter 6 Overall Synthesis

6.1 Main findings

Towards a healthy agri-food system plays an important role in advancing multiple Sustainable Development Goals (SDGs), including no poverty (SDG 1), zero hunger (SDG 2), ensuring good health and well-being for all (SDG 3), securing access to clean water and sanitation (SDG 6), and taking urgent action to combat climate change and its impacts (SDG 13). As food systems become increasingly intertwined with health, the environment, technology, and social equity, understanding the drivers and economic impacts of agri-food system changes—particularly in developing and transitional economies—has emerged as a critical area of research.

This dissertation investigates the driving factors behind a healthy agri-food system in rural China and examines their implications for both residents' health and the environment. Specifically, it analyzes how shifts in the agri-food system influence nutritional health and sustainable development in rural areas from three perspectives: income inequality, digitalization, and environmental policy. We first analyze the impact of income inequality on nutritional health from an economic perspective. Then, we examine the role of Internet use in shaping healthy food consumption and nutritional health from a technological perspective. Recognizing that healthy food consumption should also account for environmental sustainability, we further explore the impact of Internet use on the environmental footprint of food consumption from the perspective of environmental health. Finally, environmental policies can mitigate the environmental impact of food consumption, but they may also alter local agricultural factor inputs, such as land, fertilizers, and labor. Besides, achieving a healthy agro-food system requires that environmental policies generate environmental health benefits without compromising the sustainable development of agriculture. So, we also discuss how environmental policy affects agricultural TFP. The detailed findings are as follows.

First, we find that income inequality is a key driving factor influencing nutritional health in rural areas (Chapter 2). Our results show that the relationship between income and BMI among rural residents in China has shifted from a positive to a negative correlation. Rising income inequality further increases the risk of overweight and obesity. In addition, low-income and male groups are more adversely affected by income inequality. These findings highlight the importance of reducing income inequality as a strategy to mitigate the negative health consequences associated with the transformation of food consumption in rural China.

Second, we reveal that Internet use is an important factor shaping dietary quality and nutritional health (Chapter 3). On the one hand, Internet access improves rural residents' dietary knowledge, thereby enhancing overall diet quality. On the other hand, it also raises the risk of overweight and obesity, primarily due to reduced physical activity associated with increased screen time. Interestingly, while Internet use is positively correlated with higher self-rated health, it is also linked to greater risks of chronic diseases such as diabetes and hypertension. This discrepancy suggests that rural residents may lack sufficient awareness of the long-term health risks posed by chronic conditions. Overall, these findings underscore the dual role of digital transformation in shaping food consumption and health outcomes.

Third, we find that Internet use is also an important factor influencing sustainable food consumption (Chapter 4). Our results show that Internet use is associated with an 18.1% reduction in the carbon footprint and a 10.6% reduction in the water footprint of food consumption. This effect is primarily driven by reduced consumption of animal-based foods such as pork and eggs. Further heterogeneity analysis indicates that Internet use mainly influences the sustainable food consumption of younger and higher-income groups. These findings highlight the potential of digitalization as a tool to foster sustainable food consumption, while also underscoring the need for policies that ensure equitable access and benefits across different rural populations.

Last, we find that environmental policies are also a key driving force for sustainable agricultural development (Chapter 5). Our findings show that the FFCS projects have a significant positive effect on agricultural development. Specifically, FFCS increased agricultural TFP by 1.7%–2.4%, and the effect of FFCS on agricultural TFP would be underestimated if the endogeneity due to sample selection bias was not taken into account. Besides, health, savings, and industrial structure are the important channels through which FFCS projects affect agricultural TFP. Specifically, FFCS projects not only benefit health and savings but also promote the optimization of the industrial structure, thus having a positive effect on agricultural TFP. Like HRS, the effect of FFCS projects on agricultural TFP is likely to be one-off rather than sustainable. We also find that there is heterogeneity among different FFCS projects. The positive effect of international projects on agricultural TFP is greater than that of national projects.

6.2 Scientific contributions

The main scientific contributions of this dissertation are as follows:

The first research topic examines the health impacts of China's dietary transition through the lens of income inequality. This part of the study makes three main contributions. First, it explores the current state of income inequality in rural China and its relationship with nutritional outcomes in the context of a transitioning economy. Unlike most existing studies that focus on developed countries, this research contributes to the literature by providing empirical evidence from a major developing country. Second, it tests whether income inequality has a greater impact on low-income groups in rural China. To address individual heterogeneity, the study adopts the individual-level relative deprivation index rather than aggregate measures, thereby overcoming a standard limitation in existing research. Third, it aims to raise awareness of income inequality among rural residents and provide policy recommendations to improve nutrition and welfare. The findings also offer insights for other transition economies facing similar challenges.

The second topic of this dissertation explores the impact of digital transformation on food consumption and nutritional health in rural China. This section makes three key contributions. First, while most existing research focuses on urban populations, this study extends the analysis to rural areas, where evidence remains limited. Second, rather than examining only the causal relationship between Internet use and nutritional health, this study investigates the underlying mechanisms, specifically through the channels of diet quality and physical activity. Third, while digitalisation and nutrition have been widely studied in developed countries, little attention is given to this issue in developing contexts. The findings provide valuable insights not only for promoting sustainable rural development in China but also for informing food and digital policy design in other developing countries.

The third topic of this dissertation explores the impact of Internet use on sustainable food consumption. This section makes three key contributions. First, it examines Internet use from the perspective of consumption behaviour. It extends the current literature by linking two important topics: Internet use and sustainable food consumption. Second, it not only identifies the causal relationship between Internet use and sustainable food choices but also investigates the underlying channels and heterogeneity. The results show that Internet use reduces the carbon footprint of food by 18.1% and the water footprint by 10.6%, mainly due to lower consumption of animal products such as pork and eggs. These findings offer new insights into promoting sustainable diets. Third, the study focuses on rural China, where related research remains limited. Most existing studies focus on developed countries. By the end of 2016, China already had 731 million Internet users—the largest in the world. As Internet penetration continues to rise in developing countries, the findings of this study may offer valuable lessons for other countries such as India, Vietnam, and Thailand. They also provide functional policy implications for China's efforts toward sustainable development.

The last research topic analyzes the effect of the FFCS project on sustainable agricultural development. This part of the study makes two main contributions as follows. First, we developed a theoretical framework to examine the relationship between the FFCS project and agricultural development, and empirical analysis shows that FFCS projects have increased agricultural TFP by 1.7% to 2.4%. Our study assesses the impact of the FFCS project on sustainable agricultural development from the perspective of environmental policy, thereby enriching the literature on the healthy agri-food system. In addition, we investigate the channels through which the FFCS project influences agricultural TFP. To mitigate the adverse effects of human activities on climate change, several transitional economies, including India, Vietnam, and Brazil, have also implemented such projects. However, no research has yet systematically identified the unintended effects of these initiatives. As China and other countries undergo major economic transformations and face severe environmental challenges, the positive contribution of forest–agriculture cooperation projects to China's agricultural TFP offers valuable insights for other countries seeking to promote project development in line with their own conditions.

In summary, this dissertation systematically examines how income inequality, digitalization, and environmental policies influence the effects of the transformation of the agri-food system in rural China on health and the environment. The findings provide valuable insights for developing countries such as China, which are undergoing rapid socio-economic transitions and striving for a healthy and sustainable transformation of their agri-food systems.

6.3 Policy implications

This dissertation highlights the roles of income inequality, digitalization, and environmental policies in shaping a healthy agro-food system. Based on our findings, we propose the following key policy recommendations from these three perspectives.

First, policymakers could improve nutritional and health outcomes in rural China by addressing income inequality. To this end, it is important to develop policies that promote income redistribution, strengthen social safety nets, and provide targeted support for vulnerable groups. In addition, given the current lack of specific nutrition policies in rural areas, drawing on international experiences to design and implement comprehensive nutrition programs is essential. Such programs could include nutrition education, improved access to healthy foods, and regular health monitoring. Evidence also suggests that men and low-income groups are particularly vulnerable to nutritional deficiencies, and rural nutrition policies should therefore pay special attention to these populations.

Second, policymakers can promote healthier and more sustainable food consumption by enhancing digital social services in rural areas. While digitalization has improved access to information and dietary awareness, it has also increased screen time and reduced physical activity among rural residents, potentially harming overall health. Therefore, alongside expanding rural Internet infrastructure, the government should invest in sports facilities and community spaces and implement digital literacy programs that incorporate healthy lifestyle practices and self-health education in the context of Internet use. Moreover, the environmental impact of food consumption—measured by carbon and water footprints—varies significantly across income levels and age groups, highlighting the need for policies that consider socio-economic and demographic factors. For example, online educational initiatives may be more effective in fostering sustainable eating habits among younger populations, whereas offline, community-based projects may better reach older adults. Notably, Internet use does not appear to significantly reduce the food-related carbon and water footprints of low-income households, likely due to their limited food purchasing options. As income remains a key determinant of sustainable food consumption, raising the income levels of low-income families may be a more effective strategy than promoting digital engagement alone.

Finally, policymakers can foster sustainable agricultural development through environmental policies, thereby achieving a win-win situation. The implementation of the FFCS project can not only sequester carbon dioxide to mitigate global warming, but also promote the growth of total factor productivity (TFP) in agriculture. Policymakers may consider expanding the FFCS project to more counties, thereby contributing to China's carbon neutrality goals, improving agricultural TFP, and fostering economic development. At the same time, it is important to recognize that the project also affects workers' health, income, and industrial structure. Policymakers could prioritize implementing the FFCS project in areas with poor population health, low income levels, and unbalanced industrial structures, so that it benefits the local ecology while improving residents' health, income, and industrial structure. In this way, the expected spillover effects of the FFCS project may also promote agricultural development in the target areas. Finally, given the longer implementation cycle of international projects, their impact on agricultural TFP tends to be greater than that of domestic projects. Therefore, policymakers should pay more attention to ensuring the long-term effectiveness of the FFCS project. In addition, the design and supervision of domestic initiatives could draw on the experiences of international projects to further improve the quality of the FFCS project.

6.4 Limitations

This dissertation systematically examines how changes in China's agri-food system affect health and the environment, with a particular focus on income inequality, digitalization, and environmental policies, as well as the underlying mechanisms. As the world's largest developing and transitional economy, China's transformation of its agri-food system offers valuable lessons and insights for other countries facing similar challenges. With continued economic growth and rapid urbanization, many rural areas in developing countries are likely to confront comparable issues related to nutrition, health, and sustainability. In this context, China's experience provides an important point of reference for shaping global rural development policies. Nonetheless, this study also has certain limitations.

The limitations of Chapter 2 are as follows. First, we refer to existing literature to construct three individual-level income inequality indices. We run regressions and obtain consistent results. However, many other indices of individual-level income inequality are not included in the analysis. In addition, community-level income inequality measures can also be applied to this issue but are not considered. Moreover, we use data from only one year. We do not further address potential endogeneity concerns. Therefore, although our findings demonstrate that income inequality is an important factor influencing a healthy agri-food system, they provide limited evidence regarding the causal relationship between the two.

The limitations of Chapter 3 are as follows. Physical activity is measured by the number of times respondents engage in sports activities during the past week. These activities include martial arts (e.g., Kung Fu), gymnastics, dance, acrobatics, track and field (e.g., running), swimming, football, basketball, tennis, badminton, volleyball, and other forms of exercise. However, the CHNS data do not provide detailed information on the duration or intensity of each activity, which limits our ability to capture the full variation in physical activity levels. Moreover, for chronic disease-related variables, we focus only on two conditions: hypertension and diabetes. While these are prevalent and highly relevant to public health, other chronic conditions may also influence health outcomes and could provide additional insights if included.Despite these limitations, our study benefits from a large dataset of nearly 30,000 observations and the use of panel data, which allows us to control for individual heterogeneity and time-invariant factors. Therefore, we consider our results to be robust and informative, even though further research incorporating more detailed physical activity measures and additional health outcomes could strengthen the findings.

The limitations of Chapter 4 are as follows. The food environmental footprint is calculated by multiplying the amount of food consumed, including both purchased and self-produced, by the corresponding weighted environmental intensity. We extract carbon and water footprint factors for each food group from over 100 LCA studies, covering the entire life cycle from cradle to farm gate. The factors used in this study are the average values across these studies. Our data cover 12 provinces and three autonomous municipalities in China. Environmental impact factors may vary across regions, so using the same factors for all areas may not be fully accurate. However, we use panel data to analyze the impact of digitalization on the environmental footprint. This approach effectively controls for regional heterogeneity. Therefore, our results remain reliable.

The limitations of Chapter 5 are as follows. First, the study is constrained by data availability. Although we accurately estimate the impact of FFCS projects on agricultural total factor productivity (TFP) using panel data from 140 counties spanning 2002 to 2018, the analysis focuses on a single province. This limitation may reduce the national generalizability of the findings.

Future research could collect similar data from other provinces where FFCS projects have been implemented. Doing so would improve the representativeness of the results and allow for a more comprehensive assessment of the policy's effects across different regional contexts. Second, this study examines only the overall impact of FFCS projects on agricultural TFP. TFP is a complex measure that can be further broken down into components such as scale effects, technical efficiency, and technological progress. Future studies could explore how FFCS projects influence each of these components individually. This would provide a deeper understanding of the mechanisms through which FFCS projects affect agricultural productivity and could inform more targeted policy design.

6.5 Outlook and future work

First, this dissertation mainly focuses on how to achieve a healthy agri-food system in rural China from the perspectives of income inequality, digitalization, and environmental policies. However, the theoretical and empirical analyses presented in the four chapters are conducted independently. Future research could consider integrating these factors into a single analytical framework. This approach would allow for a more comprehensive assessment of how to balance human health with sustainable development.

Second, the primary data source for this thesis is the China Health and Nutrition Survey (CHNS) public database. However, survey data after 2015 have not been publicly released, and food consumption data are available only up to 2011. In addition, the questionnaire design varies across survey waves, leading to some inconsistencies. As a result, the empirical analyses in Chapters Two, Three, and Four are mainly based on data from 2004 to 2015. For Chapter 5, we use panel data from 140 counties in Sichuan Province, China, covering the period from 2002 to 2018. Despite this, the representativeness of the sample remains limited. Future research could improve the breadth and generalizability of the findings by incorporating more comprehensive micro-survey data or integrating multi-level data from a wider geographical range, such as county-level or provincial-level datasets.

Last, comparative studies on agri-food system changes between China and other countries hold significant potential for generating deeper insights. The main goals and challenges of transforming agri-food systems differ across countries. Over the past few decades, China has gradually shifted its focus from ensuring sufficient calorie intake to promoting more nutritious and environmentally sustainable diets. In contrast, many rural populations in developing countries still face the fundamental problem of food insecurity, where adequate calorie consumption remains the primary concern. However, developed countries tend to place greater emphasis on the environmental impacts of dietary changes. Environmental policies also differ widely across countries. Given these differences in development stages, future research could benefit from cross-national comparative analyses. Such studies could explore the similarities and differences in policy approaches, consumer behaviors, and environmental and health outcomes. This would provide a deeper understanding of global changes in agri-food systems and generate policy recommendations tailored to specific contexts, supporting sustainable and healthy improvements in agri-food systems for rural populations worldwide.

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Appendix

Table A3.1: Healthy eating index (HEI) for Chinese components and standard for scoring

Component	Score		
	0	5	10
Adequacy			
Fruits	0 →		≥350g
Total Grains	0 →	≥300g	
Whole Grains and Mixed Beans	0 →	≥150g	
Tubers	0 →	≥100g	
Vegetables	0 →	≥500g	
Dark Vegetables	0 →	≥250g	
Dairy	0 →	≥300g	
Soybeans	0 →	≥15g	
Fish and Seafood	0 →	≥40g	
Poultry	0 →	≥40g	
Eggs	0 →	≥40g	
Seed and Nuts	0 →	≥10g	
Limitation			
Red Meat	≥260g →	≤30g	
Cooking Oils	≥65g →		≤30g
Sodium	≥6g →		≤2g
Added Sugars	≥20 % of energy →	≤10 % of energy	
Alcohol	≥25g(men)/15g(women) →	≤60g(men)/40g(women)	

Source: Dietary Guidelines for Chinese (2016) and Yuan et al (2017).

Table A3.2: Questions concerning dietary knowledge in the CHNS

Dietary knowledge:	True/False
Do you strongly agree, somewhat agree, are neutral, somewhat disagree or strongly disagree with this statement?	
*Please note that the question is not asking about your actual habits.	
Q1: Choosing a diet with a lot of fresh fruit and vegetables is good for one's health	T
Q2: Eating a lot of sugar is good for one's health	F
Q3: Eating a variety of foods is good for one's health	T
Q4: Choosing a diet high in fat is good for one's health	F
Q5: Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health	T
Q6: Consuming a lot of animal products daily (fish, poultry, egg and lean meat) is good for one's health	F
Q7: Reducing the amount of fatty meat and animal fat in the diet is good for one's health	T
Q8: Consuming milk and dairy products is good for one's health	T
Q9: Consuming beans and bean products is good for one's health	T
Q10: Physical activities are good for one's health	T
Q11: Sweaty sports or other intense physical activities are not good for one's health	T
Q12: The heavier one's body is, the healthier he or she is	F

Index rules: "1" point was given for a correct answer, "-1" point for an incorrect answer, and "0" points for the other answers. Source: The dietary knowledge questionnaire is from the official website of the China Health and Nutrition Survey. (**http://www.cpc.unc.edu/projects/china**)

Table A4.1: Carbon and water LCA factors

	Carbon LCA factors	Water LCA factors
Grains	0.260	1.432
Beans	0.060	2.700
Tubers	0.250	0.272
Vegetables	0.450	0.366
Fruits	0.072	1.856
Dairy	1.070	1.280
Fish	3.424	1.000
Red meat	33.50	9.717
Poultry	3.250	3.971
Pork	6.470	4.445
Eggs	1.210	3.094

Notes: The author calculated the factors from the relevant literature. Literature sources are available on request from the corresponding author.

Table A5.1: Estimation results of the production function.

Variables	FE estimation	GMM estimation
Labor	0.281***	0.073
	(10.323)	(1.583)
Land	0.015	0.151*
	(0.204)	(1.904)
Fertilizer	0.155***	0.171***
	(3.787)	(3.478)
Machinery	0.260***	0.174***
	(4.053)	(2.984)
Observations	2380	2380

Notes: The mean values are presented, and the standard deviations are within parentheses; *** is p < 0.01; ** is p < 0.05; * is p < 0.1.

Table A5.2: The PSM validity test

Variables	Control group mean	Treated group mean	Difference
GDP	8.766	8.683	0.082
Area	7.72	8.026	-0.306
Fixed	11.504	11.233	0.27
Finance	11.199	10.76	0.439
Industrial	11.026	10.284	0.742
Sickbed	6.292	5.883	0.409
Irrigation	8.823	8.061	0.762
Urbanization	0.17	0.143	0.027

Notes: Data from the first year of project implementation (2006) were used for matching; *** is p < 0.01; ** is p < 0.05; * is p < 0.1.

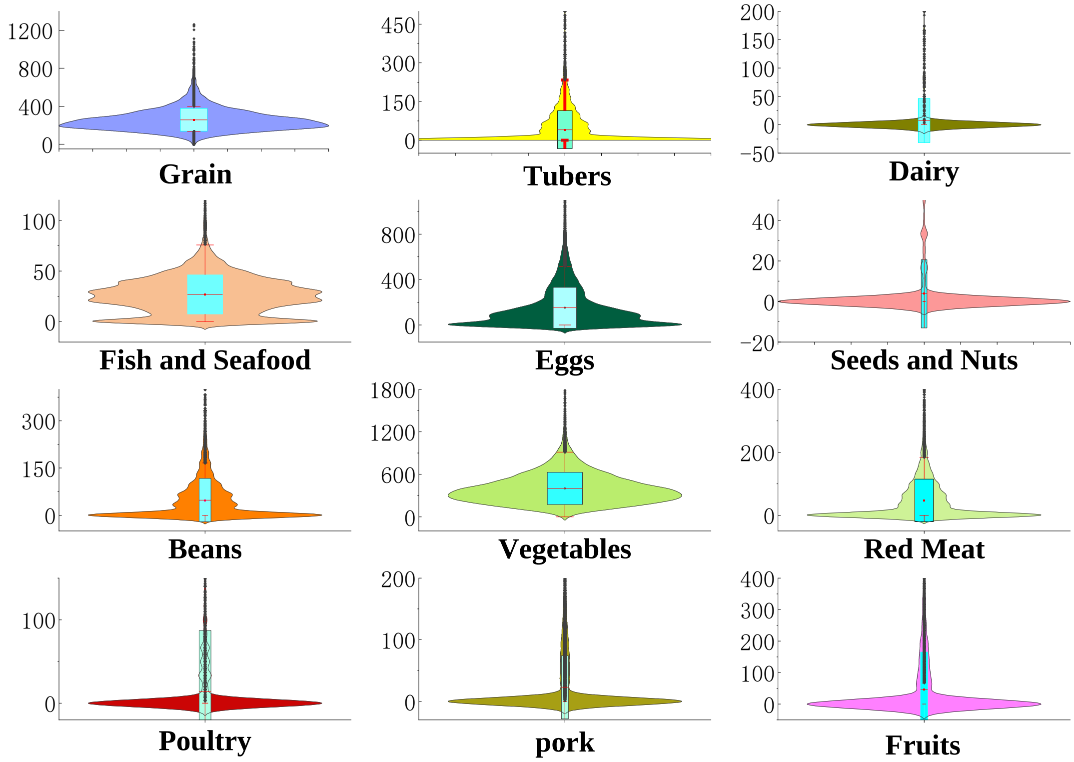

Figure A4.1: The food consumption (unit: g/capita/day) in rural China between 2004 to 2011

Note: The boxplots show the mean value and standard error, while the violin plots provide information about the distribution of food intake. Data source: Author's calculation based on the CHNS data.

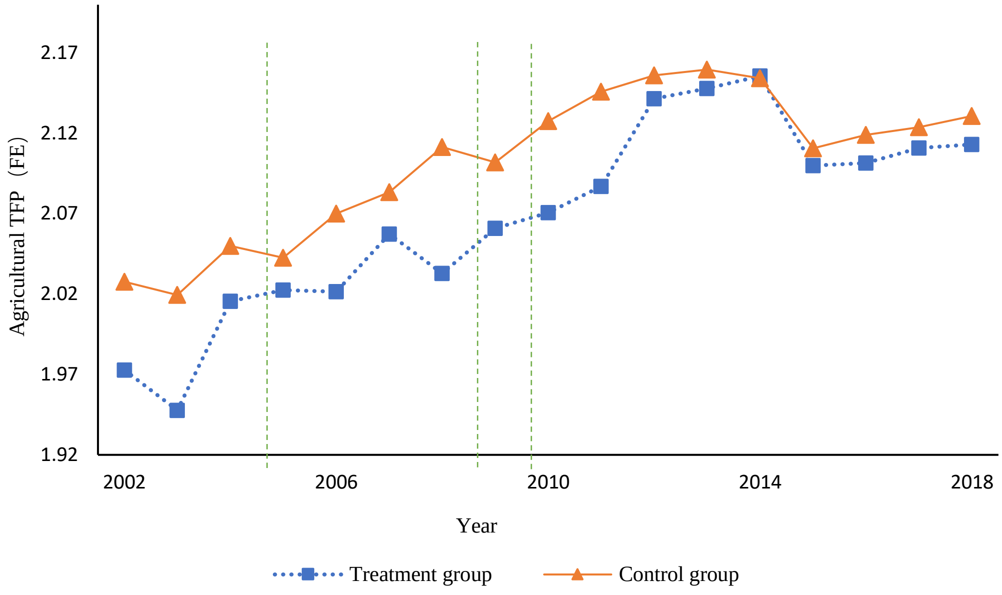

Figure A5.1(a): Parallel trend of Agricultural TFP (FE estimates)

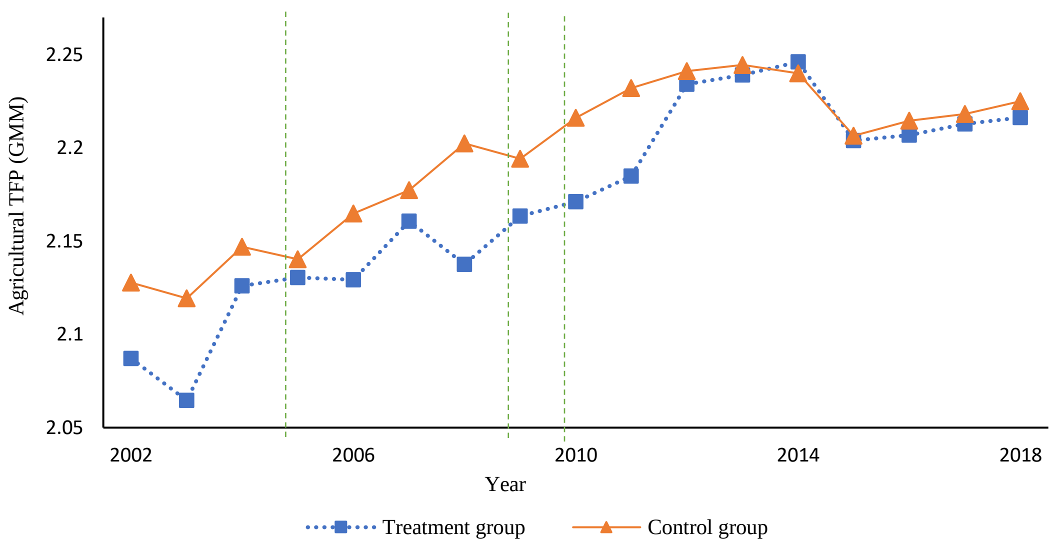

Figure A5.1 (b): Parallel Trend of Agricultural TFP (GMM estimates)

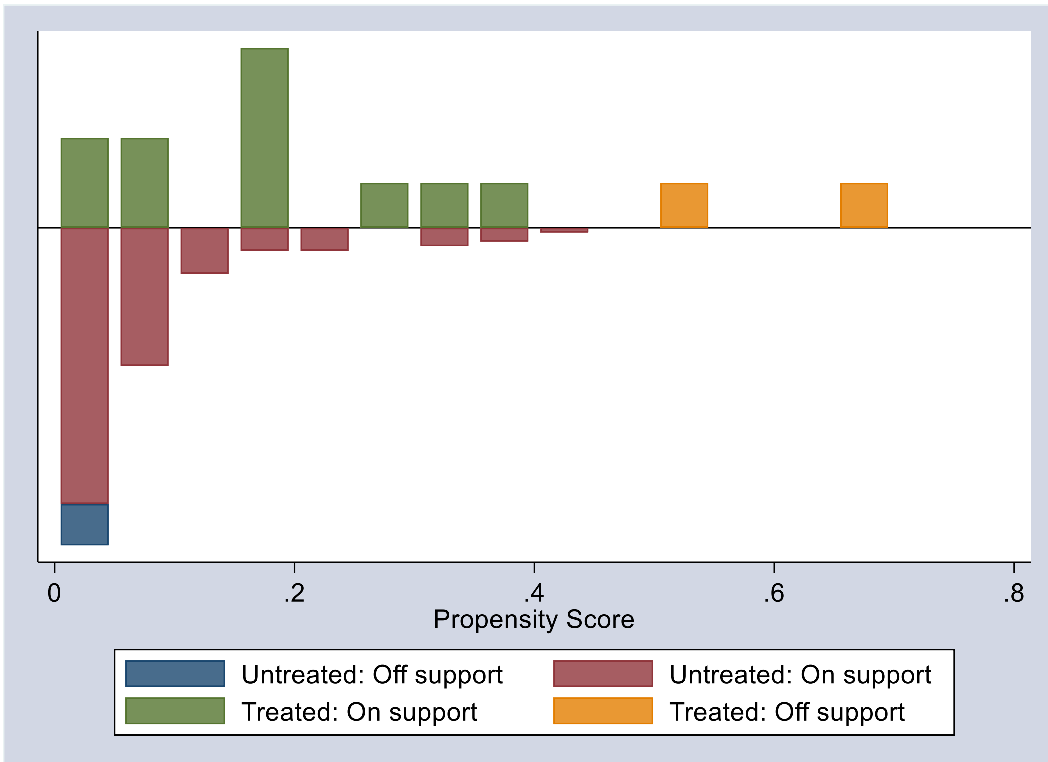

Figure A5.2: The common support area of PSM

Eidesstattliche Erklärung / Declaration under Oath

Ich erkläre an Eides statt, dass ich die Arbeit selbstständig und ohne fremde Hilfe verfasst, keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

I declare under penalty of perjury that this thesis is my own work entirely and has been written without any help from other people. I used only the sources mentioned and included all the citations correctly both in word or content.

Datum / *Date* Unterschrift des Antragstellers / *Signature of the applicant*

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Publications in English (* denotes corresponding author; + denotes co-first author)

[1] **Liu Jian**; Ren Yanjun; Hong Yu; Glauben Thomas; Qiang Li. The effect of Internet use on food consumption and its environmental footprints: Evidence from rural China. Sustainable Futures, 2025: 100466.

[2] Deng Zhilong; **Liu Jian***; Hong Yu; Liu Weigang. The effect of Internet use on nutritional intake and health outcomes: new evidence from rural China. Frontiers in Nutrition, 2024: 1364612.

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