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ESSAYS ON DRIVERS FOR SUSTAINABLE PRODUCTION OF CHINESE ARABLE FARMS

SHIJIA KANG

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Vorsitz:	Prof. Dr. Philipp Lergetporer
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Abstract

Chinese arable farming not only occupies an important position in China's agricultural sector but also serves as a cornerstone for global food security. However, this sector faces problems caused by health and safety concerns, resource constraints, and a range of environmental issues associated with the need to increase production. Addressing these challenges and ensuring sustainable agricultural development has become critical. Agricultural technology emerges as a fuel for improving sustainable intensification by enhancing efficiency and reducing environmental impacts. With this in mind, this dissertation aims to explore the drivers for sustainable production of Chinese arable farms in four empirical studies, which include information and communication technology (ICT) use, food quality certification participation, soil fertility management practices' (SFMPs) adoption, farmers' mental health, as well as several demographic and farm characteristics and environmental factors.

The first study investigates the impact of farmers' ICT use on vegetable production performance. The results reveal the difference in efficiency between ICT users and non-users through improved management techniques, highlighting the potential benefits ICT brings to vegetable production in China. The heterogeneous effect of ICT is examined to ease the design of tailor-made solutions for different subgroups of farmers. The second study shifts attention to the impact of food quality certification on farms' sustainable productivity in China. The empirical application focuses on the eco-efficiency comparisons of conventional farms and farms certified at three different levels (hazard-free, green, and organic) in arable farm production. The results indicate that, on average, certified farms are better than conventional farms in terms of combined economic and environmental performance. This suggests that food quality certification can be a helpful tool for promoting eco-efficient farming. Considering the current challenges faced by arable land, which hinders the principles of sustainable agricultural development, the third study focuses on the adoption of SFMPs. Socio-economic factors and substitution or complementary relationships between SFMPs are important predictors of adoption. Moreover, vegetable farmers increase their fertilizer productivity by adopting SFMPs. The fourth study explores the determinants that affect farmers' mental health and finds that age, education, male household head, training, trust in surroundings, and rural development are positively related to mental health, while low income is linked to poorer mental health. Additionally, heterogeneous impacts of mental health on

Chinese arable farm efficiency are moderated by education level and off-farm employment.

Overall, this dissertation suggests the significance of sustainable agricultural production and also highlights the drivers of economic as well as environmental performance in Chinese arable farms. Based on these findings, some policy recommendations can be drawn.

Zusammenfassung

Der chinesische Marktfruchtbau ist nicht nur für die chinesische Landwirtschaft von großer Bedeutung, sondern auch ein Eckpfeiler der globalen Ernährungssicherheit. Dieser Sektor ist jedoch mit Problemen konfrontiert, die sich aus der Knappheit der Ressourcen und einer Reihe von Umweltproblemen ergeben, die mit der Forderung nach einer Produktionssteigerung einhergehen. Die Bewältigung dieser Herausforderungen und die Gewährleistung einer nachhaltigen landwirtschaftlichen Entwicklung sind von größter Bedeutung. Hierbei nimmt die verwendete Produktionstechnologie eine zentrale Rolle ein, da sie den Motor zur Verbesserung der nachhaltigen Intensivierung darstellt, indem sie die Effizienz steigert und die Umweltauswirkungen mildert. Vor dem Hintergrund dieses Spannungsverhältnisses zielt diese Dissertation darauf ab, die Triebkräfte für eine nachhaltige Produktion in chinesischen Ackerbaubetrieben in vier empirischen Studien zu erforschen. Dazu gehören der Einsatz von Informations- und Kommunikationstechnologie (IKT), die Teilnahme an einer Zertifizierung der Lebensmittelqualität, die Anwendung von Bodenfruchtbarkeitsmanagementpraktiken, die psychische Gesundheit der Landwirte sowie verschiedene demographische und betriebliche Merkmale sowie Umweltfaktoren.

In der ersten Studie werden die Auswirkungen der IKT-Nutzung durch Landwirte auf die Performance in der Gemüseproduktion untersucht. Die Ergebnisse zeigen den Unterschied in der Effizienz zwischen IKT-Nutzern und Nicht-Nutzern durch verbesserte Managementtechniken, was den potenziellen Nutzen der IKT für die Gemüseproduktion in China unterstreicht. Die heterogene Natur der Auswirkungen von IKT wird untersucht, um die Entwicklung von maßgeschneiderten Lösungen für verschiedene Untergruppen von Landwirten zu erleichtern. Die zweite Studie widmet sich den Auswirkungen einer Teilnahme an einem Zertifizierungsprogramm zur Steigerung der Lebensmittelqualität auf die nachhaltige Produktivität landwirtschaftlicher Betriebe in China. Die empirische Anwendung konzentrierte sich auf den Vergleich der Ökoeffizienz von konventionellen Betrieben und Betrieben mit drei verschiedenen Zertifizierungsniveaus (“harmlos“, „grün“ und „ökologisch“) im Marktfruchtbau. Die Ergebnisse zeigen, dass zertifizierte Betriebe in Bezug auf die kombinierte wirtschaftliche und ökologische Leistung im Durchschnitt besser sind als konventionelle Betriebe, was darauf hindeutet, dass die Zertifizierung der Lebensmittelqualität ein nützliches

Instrument zur Förderung einer ökoeffizienten Landwirtschaft sein kann. Angesichts der zunehmenden Anforderung einer nachhaltigen Bewirtschaftung landwirtschaftlicher Flächen, konzentriert sich die dritte Studie auf die Nutzung verschiedener Maßnahmen zur Steigerung einer nachhaltigen Bodenfruchtbarkeit. Die Analyse zeigt, dass die sozioökonomischen und die Substitutions- oder Komplementärbeziehungen zwischen den Praktiken wichtige Prädiktoren für die Einführung sind. Darüber hinaus erhöht die Nutzung der nachhaltigen Praktiken die Produktivität eingesetzten Düngemittel. Die vierte Studie untersucht die Prädiktoren für die psychische Gesundheit von Landwirten und kommt zu dem Ergebnis, dass Alter, Bildung, das Vorhandensein eines männlichen Haushaltsvorstands, Ausbildung, Vertrauen in die Umgebung und ländliche Entwicklung positiv mit der psychischen Gesundheit assoziiert sind, während ein niedriges Einkommen mit einer schlechteren psychischen Gesundheit verbunden ist. Darüber hinaus verbessert die psychische Gesundheit die Effizienz chinesischer Ackerbaubetriebe, was durch das Bildungsniveau und die Teilnahme an außerlandwirtschaftlichen Aktivitäten moderiert wird.

Insgesamt unterstreichen die Ergebnisse dieser Dissertation die Bedeutung einer nachhaltigen landwirtschaftlichen Produktion und identifiziert mehrere Stellgrößen, um die ökonomische und ökologische Leistungsfähigkeit von chinesischen Ackerbaubetrieben zu steigern. Die Dissertation gibt zudem Hinweise hinsichtlich geeigneter Politikmaßnahmen, um dieses Ziel zu erreichen.

Content

List of figures

List of tables

List of abbreviations

BMEL	Bundesministerium für Ernährung und Landwirtschaft
DEA	Data Envelopment Analysis
EE	Eco-efficiency
FAO	Food and Agriculture Organization of the United Nations
ICT	Information and Communication Technology
MESR	Multinominal Endogenous Switching Regression
MVP	Multivariate Probit
OECD	Organization for Economic Co-operation and Development
PGT	Pressure-generating Technology
PSM	Propensity Score Matching
SFA	Stochastic Frontier Analysis
SFMP	Soil Fertility Management Practice
TE	Technical Efficiency
WBCSD	World Business Council for Sustainable Development

1. Introduction

This dissertation is concerned with drivers for sustainable production by Chinese arable farms. Chinese arable farmers, as farmers worldwide, face challenges posed by the need to increase yields and a range of environmental issues associated with agricultural production. This section reviews these challenges, as well as the general characteristics of the arable farming system in China. Subsequently, the relevance of technology and sustainable productivity in this context is discussed, and the aims of this dissertation are presented in more detail.

1.1 Overview of the Chinese arable farming sector

Arable farming is one of the main components of agriculture. Its characteristics are producing on land and using the biological functions of crops to convert solar energy into chemical energy and agricultural products (BMEL, 2019). In arable farms, a wide variety of crops are grown, including cereals, cash crops, vegetables, green manure crops, and various horticultural varieties (FAO, 2022). Its products are not only the main source of food and living materials for human survival but also directly or indirectly promote the development of other industries. For example, it provides raw materials for the textile and food industries, as well as feeds for animal husbandry and fisheries (Ritchie and Roser, 2019).

China is a predominantly agricultural country, and its arable farming has a long history that can be traced back to the Neolithic period. Along with the changes in times and social development, arable farming in China has become one of the important foundations of China's economy. According to data from the National Bureau of Statistics of China, as of 2022, the total output value of China's arable land has reached 8.4 trillion yuan. Compared with 5.2 trillion yuan in 2014, it has increased by 62.8%. The total agricultural output value created by arable land accounts for nearly 54.1% of the total output value of agriculture (including cultivated land, forestry, animal husbandry, and fishery). This important share shows the prominent position of arable land in China's agriculture.

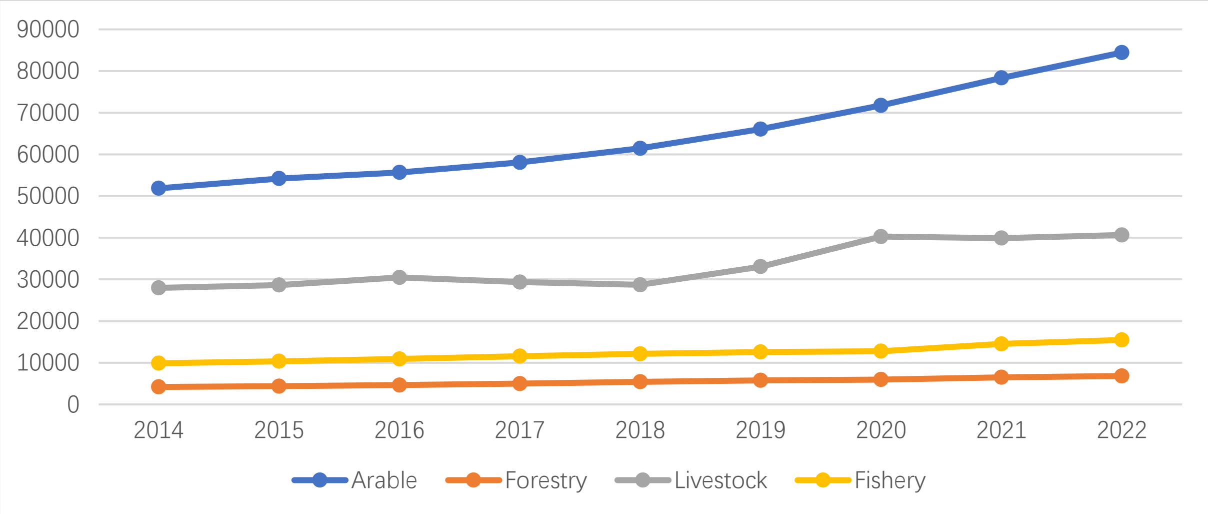

Figure 1-1 Trend of gross product by agricultural subsector from 2014 to 2022 (Unit: billions of yuan).

Source: National Bureau of Statistics https://data.stats.gov.cn/easyquery.htm?cn=C01

Chinese arable farms also hold a significant position within the global food system. According to the United Nations Food and Agriculture Organization (FAO, 2022), China has approximately 1.1 billion hectares of arable land (see Figure 1-2). That is, Chinese arable farms feed about 20% of the world's population with 9% of the Earth's total land area (Cui and Shoemaker, 2018). Due to the great emphasis on opening its agricultural sector to the global market, China has established increasingly close connections with other countries in this field. The country now maintains exchanges and cooperation with major international agricultural and financing organizations and more than 140 countries, and is a key link in the global agricultural system (FAO, 2024).

When comparing Chinese arable farms to those in other countries, several distinguishing characteristics exist: Firstly, they are characterized by small farming households with little acreage per farmer (Zou and Mishra, 2024). Although China has a large total arable land area, due to the large population base, the per capita arable land area is relatively small, only 0.08 hectares per person, which is less than 40% of the world average (FAO, 2023). Secondly, these farms emphasize more on realizing self-sufficiency than economic benefits (Ghose, 2014). Thus, agricultural production primarily aimed at meeting the family's subsistence and living needs. The smallholder incomes associated with these farms are unstable (Yang, 2009). Thirdly, there is a relatively low level of technology adoption, often lacking advanced production techniques and management experience in agricultural practices, resulting in a long-term dilemma of inefficiency in the production process (Hu et al., 2022). Lastly, the arable farms are generally located in remote areas. Farmers generally have low education levels and a weak understanding of knowledge related to ecological and environmental protection. These characteristics pose both challenges and opportunities for sustainable development within the sector.

Among the arable farms, vegetable production in China is a noteworthy sector. It is the second largest sector in arable crop production after grains. Occupying an important position in agriculture, Chinese vegetable farms directly affect food security and sustainability at home and abroad. According to data from the National Bureau of Statistics, as of 2022, China's vegetable planting area amounted to approximately 22,375 thousand hectares. It has become a large vegetable producer, with an output ranking among the world's top. Moreover, China is also a leading international exporter of vegetables, accounting for 14% of the global vegetable export volume every year. In 2022, the "China Agricultural Outlook Report" stated that China's vegetable exports amounted to 11.83 million tons, valued at 17.22 billion U.S. dollars. This accounts for about 20% of the country's total agricultural export value.

As part of arable farming, China's vegetable production has both common characteristics and its own unique features. For example, vegetable production requires more labor for sowing, managing pests and diseases, and harvesting, as well as higher agricultural (capital) expenditures, including facilities such as greenhouse cultivation (Chang et al., 2011). Vegetable farmers need to learn to make efficient use of resources. Given the increasing daily demand for vegetables and their high level of commercialization, challenges such as the harmful effects of vegetable production on soil fertility and the environment have also risen (Kianpoor Kalkhajeh et al., 2021). In addition, an increasing number of varieties and corresponding cultivation technologies have emerged in the field of vegetable cultivation. These require farmers to have a high level of learning ability and management expertise (Cai et al., 2022). Based on these considerations, it is necessary to explore the development and challenges of vegetable farming under the goal of sustainable agricultural development in China.

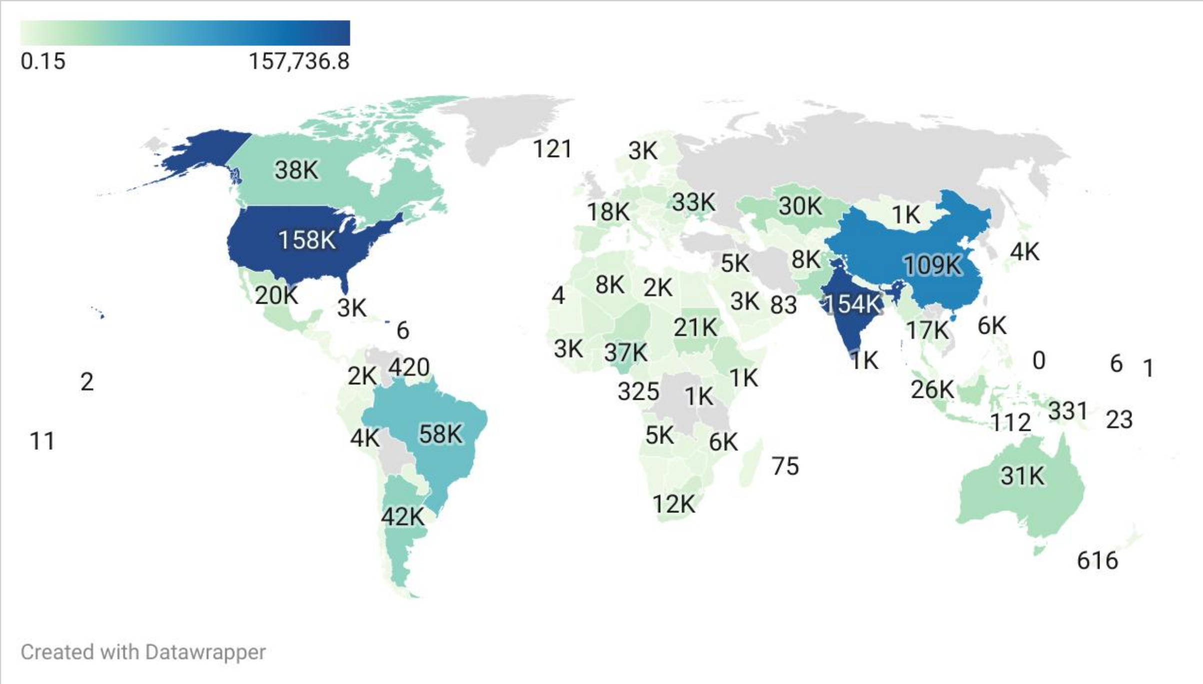

Figure 1-2 Arable land by country 2021 (Unit: hectares).

Source: UN data https://data.un.org/Data.aspx?d=FAO&f=itemCode%3A6621

1.2 The significance of sustainable productivity growth and its drivers

Productivity refers to a ratio of a volume measure of output to a volume measure of input use (OECD, 2001). Understanding and evaluating efficiency are based on this concept, which forms the foundation for subsequent measurement. At the arable farm level, productivity measures the amount produced by a farm given a set of inputs such as land, labor, and capital. To meet the increasing global demand for food and other rural and farm-based goods and services, agricultural productivity growth is seen as a powerful engine that can increase food production without using more resources (Hemathilake and Gunathilake, 2022). By increasing productivity, arable farms can produce more agricultural products, such as cereals, vegetables, and so on, with the same or even fewer inputs. These products generate considerable income for the farmers and also provide a material basis for other industries, thus contributing to the overall economic growth of the country (Pingali, 2007).

However, over the past decades, arable farmers have increased yields by using chemical fertilizers and pesticides to replenish the soil with micronutrients (i.g., nitrogen, phosphorus, and potassium) and protect crops from pests and diseases. Additionally, they have also tried to make efficient use of the arable land through multiple plowing, thus achieving more harvests (Wilson and Tisdell, 2001). In the short term, these production practices pay dividends in terms of productivity growth. However, they also cause irreversible environmental damage (Sharma and Singhvi, 2017). For instance, excessive use of chemicals such as pesticides and fertilizers leads to chemical residues in soil and water. This may lower the quality of natural resources and pollute the environment. Overcultivation of arable land results in soil erosion and a decline in soil quality (Lal et al., 2007). In addition, degradation of air quality and residues of harmful substances in agricultural products pose certain threats to human life and health (Lu et al., 2015). In the long run, agricultural production at the expense of the environment is not conducive to long-term productivity growth.

Sustainable productivity is proposed to guard against the potential unintended negative environmental impacts of productivity growth and leverage the benefits of productivity growth (Vishnoi and Goel, 2024). It rests on the principle that to meet the needs of the present without compromising the ability of future generations to meet their own needs (Brodt et al., 2011). In order to achieve sustainable productivity, arable farming needs to consider economic benefits, environmental health, and social impacts during agricultural production (Rasul and Thapa, 2004). This includes protecting soil and water resources, as well as lowering the use of chemical pesticides and fertilizers while increasing yields (Petersen and Snapp, 2015). Besides, sustainable production should also focus on the needs of farmers' groups. Considering improving social stability and farmers' well-being, more policies are put forward aiming to create a positive community environment (Bacon et al., 2012). In recent years, sustainable agricultural production has become a global political goal. For example, the EU's "Farm to Table Strategy" was put forward to accelerate the transition to a sustainable (i.e., fair, healthy, and environmentally friendly) food system. China's "National Agricultural Sustainable Development Plan" and other initiatives have been proposed. They are committed to developing a sustainable, competitive, and profitable agricultural industry that contributes to the improvement of livelihoods.

Agricultural technology has long been regarded as an effective way to increase farm productivity. It is a broad term used here to describe equipment, genetic material, farming techniques, etc., developed to achieve input savings per unit of output or produce higher-quality output (Ruzzante et al., 2021). By implementing sustainable agricultural technologies, it is possible to ensure that agricultural production is efficient without causing long-term negative impacts on environmental and social development (Adenle et al., 2019; Temple et al., 2011). Following Tripp (2001), examples of agricultural technologies in arable farming that promoted sustainable productivity in the last century include improvements with respect to biological innovations (e.g., organic pesticides and fertilizers), physical inputs (e.g., fertigation and irrigation equipment), and management techniques (e.g., information and communication technology).

As these technologies emerge and spread, arable farmers are required to decide whether to adopt one of them. Rogers (1983) defines adoption as “the decision to make full use of an innovation as the best course of action available.” Given that farmers are rational economic agents seeking to maximize utility (profit), their adoption decisions may be influenced by many factors (Feder and Umali, 1993). Extensive research over the years has categorized these factors into several key points: 1) Farmer characteristics, including age (Adams et al., 2021), gender (Mishra et al., 2020), education level (Paltasingh and Goyari, 2018), farming experience (Ainembabazi and Mugisha, 2014) of the household head; 2) Farm characteristics, including land size (Brown et al., 2020), land tenure (Soule et al., 2000), labor force (Mukasa, 2018), non-agricultural income (Nigussie et al., 2017); 3) Socio-economic and environmental characteristics, including extension services (Pan et al., 2018), cooperatives (Abebaw and Haile, 2013), training (Nakano et al., 2018), social capital (Hunecke et al., 2017; Maertens and Barrett, 2013), and natural disasters (Huang et al., 2015).

Apart from the adoption of technology, recent research has noted a shift from focusing primarily on external drivers of productivity to an increased emphasis on internal drivers. Among them, mental health is found to improve the quality of labor supply and workers’ creativity and innovation performance (Daud et al., 2020; Siddique et al., 2020). For arable farm production, farmers with better mental health have a more positive attitude to adopt new production technologies and to be involved in sustainable farming practices, which in turn enhances their sustainable productivity (Hounsome et al., 2006).

Therefore, it is necessary to ensure sustainable productivity growth as well as the adoption of advanced technological innovation and environmentally friendly practices, not only to meet current demand but also to benefit future generations.

1.3. Objectives and structure

The significance of sustainable productivity growth and technology adoption for farmers’ incomes, national economies, and overall social impact has been explored by previous researchers in extensive studies. However, most research mainly focused on the drivers for agricultural productivity in terms of economic benefits, lacking comprehensive evaluations of the impact of technology adoption on farm performance from both economic and environmental perspectives.

Existing research has explored common factors influencing technology adoption, but because of different policies and natural environments, the relationship between technology adoption and farm performance may not be consistent. These specific conditions require consideration of heterogeneity and differentiated analyses when addressing specific issues regarding sustainable agricultural production within the context of Chinese arable farms.

Additionally, given the increasing emphasis on the internal driver for sustainable production, this research also focuses on the role of farmers' mental health in efficiency improvement. Therefore, the following specific research questions are fundamental to valuing the drivers for sustainable production among Chinese arable farms:

1. What factors influence vegetable farmers' adoption of Information and Communication Technology (ICT) in China? How does it impact Chinese farmers' technical efficiency?
2. What are the determinants of Chinese farmers' adopting different levels of food quality certifications? Do food quality certifications improve economic and environmental performance compared to conventional farms?
3. What is the adoption pattern of soil fertility management practices in China? How does the implementation of these practices affect farmers' fertilizer productivity?
4. What demographic and farm characteristics impact the mental health of farmers in China's arable production? How is mental health related to farmers' technical efficiency?

Against the background of evolving Chinese arable farm production and technology adoption, the first study examines the impact of farmers' ICT use on vegetable production performance. By using farm-level survey data that accurately measures ICT adoption, this study identifies the factors influencing the farmers' adoption and the impact on their technical efficiency. The heterogeneous effect of ICT on TE is examined to facilitate the design of adapted solutions for different farmer subgroups.

The second and third studies shift the focus to environmentally targeted technology. The second study explores the impact of food quality certification (hazard-free, green, and organic certification) on farm-level eco-efficiency. It aims to understand and evaluate farmers' performance from both environmental and economic perspectives after adopting sustainable practices in their agricultural production. The role of demographic and farm characteristics in determining farms' eco-efficiency and farmers' adoption of different certifications is also considered.

The third study investigates four soil fertility management practices (soil testing, subsoiling, fertigation, and straw returning) that are now prevalent in Chinese arable farms. By analyzing farmers' decisions to invest in multiple soil fertility management practices, this study identifies complementary or substitutional relationships between the practices, as well as various factors that influence the probability and extent of soil fertility management practice adoption. The relationship between these sustainable practices and fertilizer productivity is further researched.

The fourth study regards mental health as a driver of productivity growth for Chinese arable farms and analyzes predictors that influence farmers' mental health and their technical efficiency. Further analysis of the heterogeneous effect of mental health on performance among diverse demographic groups provides a deeper understanding of the relationship between farmers' mental health and their sustainable productivity.

Before all empirical studies are presented in full detail, the following chapter 2 discusses the conceptual framework adopted in this dissertation, outlining relevant production analytical concepts and their links to drivers, as well as empirical performance measurement. Chapter 3 introduces the econometric estimation strategies. Summaries of the four studies can be found in chapter 4. Chapter 5 finally discusses the findings and gives conclusions.

2. Conceptual framework

This chapter reviews the concepts and theoretical framework employed in this dissertation. Since the research work presented in this dissertation makes use of production economics and efficiency analysis, fundamental concepts in this respect are laid out as follows.

2.1 The production function

The production function is defined as the base function for analyzing a production process, describing how inputs are transformed into outputs, and has been considered as a kind of the foundation of theoretical production analysis (Coelli et al., 2005). Assume that arable farmers use a vector of inputs ($\boldsymbol{x}$) to produce an output (y) through a vector of efficiency factors (a) described by a well-behaved production function (see Figure 2-1):

$$y = a * f(\boldsymbol{x}) \qquad (2-1)$$

Associated with the production function are several properties:

(1) Nonnegativity: The value of $f(\boldsymbol{x})$ is a finite, non-negative, real number;

(2) Weak Essentially: The production of positive output is impossible without the use of at least one input;

(3) Nondecreasing in $\boldsymbol{x}$ (or monotonicity): Additional units of input will not decrease output;

(4) Concave in $\boldsymbol{x}$: Any linear combination of the vectors. $\boldsymbol{x}^0$ and $\boldsymbol{x}^1$ will produce an output that is not less than the same linear combination of $f(\boldsymbol{x}^0)$ and $f(\boldsymbol{x}^1)$.

This production function summarizes the essence of a farm's production activities and integrates input factors such as capital, labor, land, and materials, as well as efficiency factors. Land serves as the foundation of agricultural production, including the natural resources used to create agricultural products (Wild, 2003). It directly affects both the yield and quality of crops. Labor refers to the effort that people contribute to production, including family and/or hired labor (Dupraz and Latruffe, 2015). Its quantity and quality determine the scale and efficiency of agricultural production. Capital includes the tangible assets that are used in the production process, such as machinery, equipment, and buildings. It can achieve improved timeliness of farm operations and efficient use of other inputs such as labor and land (Cornia, 1985; Sheahan and Barrett, 2017). Seeds are the basis of crop growing. Pesticides refer to chemical or biological agents used to prevent and control pests, diseases, and weeds. Fertilizers supplement soil nutrients and promote the growth and development of crops. They are essential components of materials in agricultural production (Rivera et al., 2017). Additionally, efficiency factors (e.g., adopting sustainable agricultural practices) play a key role in shaping the production function and its sustainability outcomes (Jerzmanowski, 2007).

Production performance is determined by changes in technical relations of inputs or modifications in efficiency factors. Its change is usually depicted as an alteration of the analytical function of production or an upward shift of the function (Bezat-Jarzębowska and Rembisz, 2013).

2.2 Productivity and efficiency

To measure production performance, I start out with a simple representation of the production frontier, which represents the maximum output that can be obtained from each input level (Figure 2-1). Productivity is measured by the ratio of (aggregated) output over (aggregated) input and by the slope of a ray passing through the origin and a particular data point (as indicated by the ray OA). The feasible production set consists of all points between the production frontier and the x-axis. Based on this, Farrell (1957) proposed that technical efficiency (TE) refers to the ability to obtain maximal output from a given set of inputs. Following Shephard (1970), TE can be defined as:

$$TE = \frac{y}{y^*} \Leftrightarrow y = y^* * TE \qquad 0 \leq TE \leq 1, \qquad (2-2)$$

where y is the observed output and y^* is the maximum attainable output with the observed input x.

In Figure 2-1, the points on the frontier (B and C) are technically efficient (relative to the frontier), and the points below the frontier (A) are not technically efficient because a greater amount of output can be achieved with the same input level (B) or inputs can be saved without compromising the level of output (C). Therefore, achieving higher technical efficiency requires either increasing output with current inputs (e.g., A moves to B) or reducing inputs with the existing output (e.g., A moves to C).

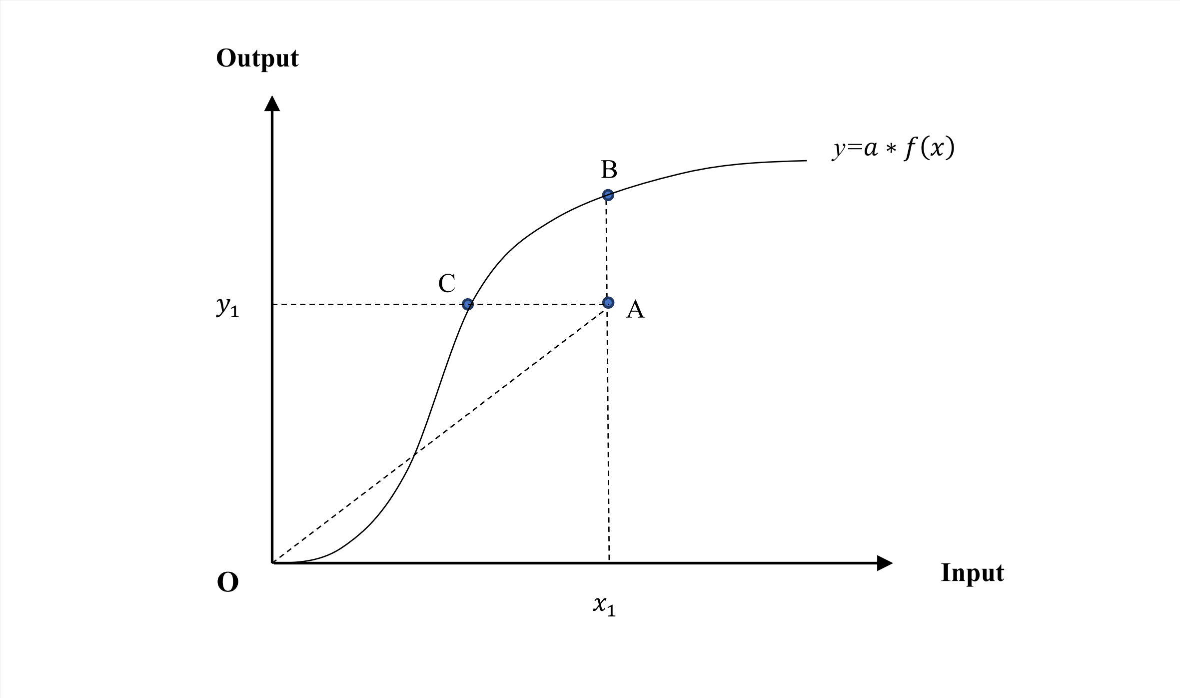

Figure 2-1 Productivity and efficiency.

Source: Adapted from Coelli et al. (2005).

2.3 Eco-efficiency

Under the requirement of sustainable development, a relatively new approach divides inputs into two specific categories: desirable inputs and undesirable inputs (Wojcik et al., 2017). Desirable inputs include traditional factors of production, such as labor and capital, which directly contribute to the output. In contrast, undesirable inputs include factors that may cause environmental pressure. While these inputs initially contribute to outcomes, they might bring long-term costs to society and the environment (Godoy-Durán et al., 2017). For example, chemical pesticides and fertilizers applied in arable farm production penetrate into soil and water and are hard to degrade (Rasul and Thapa, 2004). They can also contribute to greenhouse gas emissions (e.g., carbon dioxide, methane, nitrous oxide), along with other potential nutrient losses in the environment (Wu et al., 2021). Therefore, to measure the sustainability of arable farm production, it is necessary to distinguish between good and bad inputs.

As the concept of TE discussed in Section 2.2 does not take into account the potential environmental impacts generated during the production process, researchers started to account for this with a new concept – eco-efficiency. Eco-efficiency, introduced by the World Business Council for Sustainable

Development (WBCSD, 2000), provides a base for the assessment of both economic and environmental performances in one combined measure. It is defined by the OECD (1998) as "the efficiency of using ecological resources to meet human needs," measuring the ability to achieve economic results by making minimum use of natural resources and with the least possible environmental degradation.

Over recent decades, researchers have used the above-mentioned eco-efficiency concept in the farming context by adopting a variety of strategies (Beltrán-Esteve et al., 2017; Georgopoulou et al., 2016; Godoy-Durán et al., 2017; Gómez-Limón et al., 2012; Grassauer et al., 2021; Ho et al., 2018; Müller et al., 2015; Saber et al., 2021). One approach to applying the concept to empirical measurement has been developed by Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011) starts with the pressure-generating technology set (PGT), which describes how environmental pressures (p) are transformed into economic returns (v):

$$PGT = \{(v,p) \in R_{+}^{1+N} \,|\, \text{Value added } v \text{ can be generated with environmental pressure } p\} \quad (2-3)$$

Accordingly, eco-efficiency (EE) can be formulated as a ratio between economic value added (v) and environmental pressure (p) in Equation (2-4):

$$EE = \frac{Value\ added\ (v)}{Environmental\ pressure\ (p)} \quad 0 \leq EE \leq 1, \qquad (2-4)$$

Based on the PGT, eco-efficiency evaluates the ability of firms to generate a higher level of economic returns at a given level of environmental damage, or conversely, to generate a given level of economic returns with less environmental damage. Figure 2-2 illustrates this concept, which is very similar to the traditional production function and TE concept presented above. Point A is eco-inefficient with respect to economic returns because it could generate higher economic returns with the same amount of environmental pressure, which is reflected by the potential movement from A to B. Point A is also eco-inefficient with respect to environmental pressure because it could cause less environmental pressure to generate the same level of economic returns, which is reflected by the potential movement from A to C.

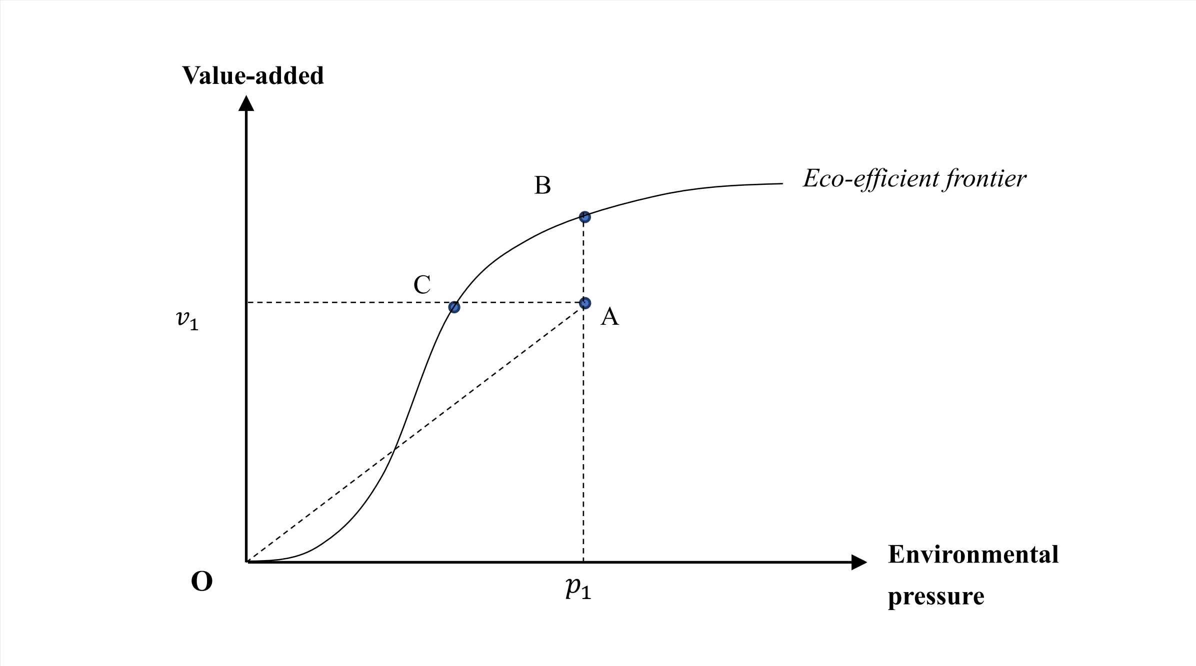

Figure 2-2 Illustration of eco-efficiency.

2.4 Drivers for sustainable production

As mentioned in the last section, new technology plays an essential role in agricultural production as an important fuel for efficiency. The adoption of new technology by farmers is a multifaceted process that is influenced by various factors. Economics theory says that rational agents make decisions and take action for utility maximization. Assume that the arable farm household maximizes an expected utility function when facing the decision to adopt a certain technology (Jongeneel et al., 2008). Let U_0 represent the benefits that farmers receive if they do not adopt the technology, and U_k represent the benefits of adopting the technology. Additionally, it is assumed that a farmer is more likely to adopt the technology if the expected benefit from adoption (Y^*) is greater than that from non-adoption, which means $Y^* = U_k - U_0 > 0$. The expected utility function approach makes it possible to introduce all dimensions in the framework as explicit factors in explaining arable farmers' sustainable production (Donkor et al., 2019; Muriithi et al., 2018).

Feder and Umali (1993) summarized factors that, in theory, can affect adoption of new agricultural technology, including access to information, farm size, family and hired labor, farmers age and education, farm tenure security, etc. Lee (2005) and Maertens and Barrett (2013) identified the role of institutions, social network and collective action in the diffusion of new technologies for agricultural sustainable development. These factors in literature have been classified as household, farm and socio-economic and environmental (Abebaw and Haile, 2013; Adams et al., 2021; Ainembabazi and Mugisha, 2014; Brown et al., 2020; Huang et al., 2015; Hunecke et al., 2017; Maertens and Barrett, 2013; Mishra et al., 2020; Mukasa, 2018; Nakano et al., 2018; Nigussie et al., 2017; Paltasingh and Goyari, 2018; Pan et al., 2018; Soule et al., 2000), which form the basis for this dissertation to examine how different characteristics interlink with production behavior and performance. Specifically, they include a) the household head's age, gender, education level, farming experience, and family burden ratio of the household; b) farm characteristics, such as land size, tenure, labor force, and off-farm income; and c) socio-economic and environmental characteristics, such as extension services, cooperatives, training, social capital, and natural disasters. A comprehensive understanding of these multifaceted influences may provide valuable insights for putting forward targeted agricultural policy recommendations in promoting effective technology adoption among farmers. Thus, the utility function $g(\cdot)$ for a household may be specified as:

$$Y^* = g(H, F, E) \qquad (2-5)$$

where Y^* is a latent variable representing the net benefit that the farmer derives from the adoption; and H, F, E represent the sets of household characteristics, farm characteristics, and social-economic and environmental factors, respectively.

In terms of agricultural production, technologies adopted by arable farmers can be classified into three primary types: biological innovations, physical inputs, and management techniques (Tripp, 2001). Over time, the contents of these technologies have been updated in response to changing policies and natural environments. Biological innovations include organic fertilizers, pesticides, new seed varieties, etc. Using organic inputs aims to lower environmental pollution and improve soil health. Advanced seeds can enhance the quality and quantity of agricultural products for human needs. Besides, some may also lead to increased crop yields with reduced resource inputs, thereby improving sustainable productivity (Rasul and Thapa, 2004). Food quality certification is one of the practices that take both food safety and environmental impacts into consideration, aiming to ensure human health as well as long-term agricultural sustainability (Bellassen et al., 2022).

Physical inputs, including soil fertility management equipment and modern machinery, also contribute significantly to the sustainable production of arable farms. For example, the advanced fertigation mixes irrigation water and fertilizer and allows an accurate and uniform application of nutrients to the roots of crops during the growing season (Jat et al., 2011). The implementation improves fertilizer supply efficiency while conserving water resources and reducing irrigation costs. Similarly, the use of mechanized farming technologies reduces labor intensity and increases operational efficiency (Zou and Mishra, 2024). This results in higher yields with less resource waste, thus bringing both economic and environmental outcomes.

The emergence of modern management techniques, such as information and communication technology (ICT), improves farmers' agricultural production skills and knowledge, which could further enhance the adoption of sustainable agricultural practices (Ma and Wang, 2020). By using digital technologies, arable farmers gain access to online platforms and tools that ease communication with experts and peers. ICT could also provide time data about soil, plants, climate, and weather so that farmers have the information needed to make rational decisions (El Bilali et al., 2020).

Apart from the technology, as discussed in Section 2.1, there is a growing recognition of the significant role that mental health plays in sustainable agricultural production. This may be because, firstly, mental health can impact behaviors such as attendance and absenteeism, thus increasing farmers' working hours (Isham et al., 2021). Besides, mentally healthy farmers are more likely to make hard decisions in agricultural production, including the adoption of new technologies and management practices (such as rational use of fertilizers and pesticides, adoption of water-saving irrigation techniques, etc.), to promote improved crop yields and quality (Bukchin and Kerret, 2020). In addition, mentally healthy farmers prefer to be involved in cooperation and knowledge sharing, which helps them produce more efficiently (Liang et al., 2022).

On the whole, both adopting technology and improving the mental health of arable farmers have the potential to realize sustainability by improving production efficiency and reducing environmental impacts. Therefore, a comprehensive understanding of these drivers and their functions in sustainable productivity is essential for putting forward effective agricultural policies in the face of current challenges for Chinese arable farms.

Figure 2-3 schematically depicts the conceptual framework regarding the drivers of sustainable productivity considered in this dissertation.

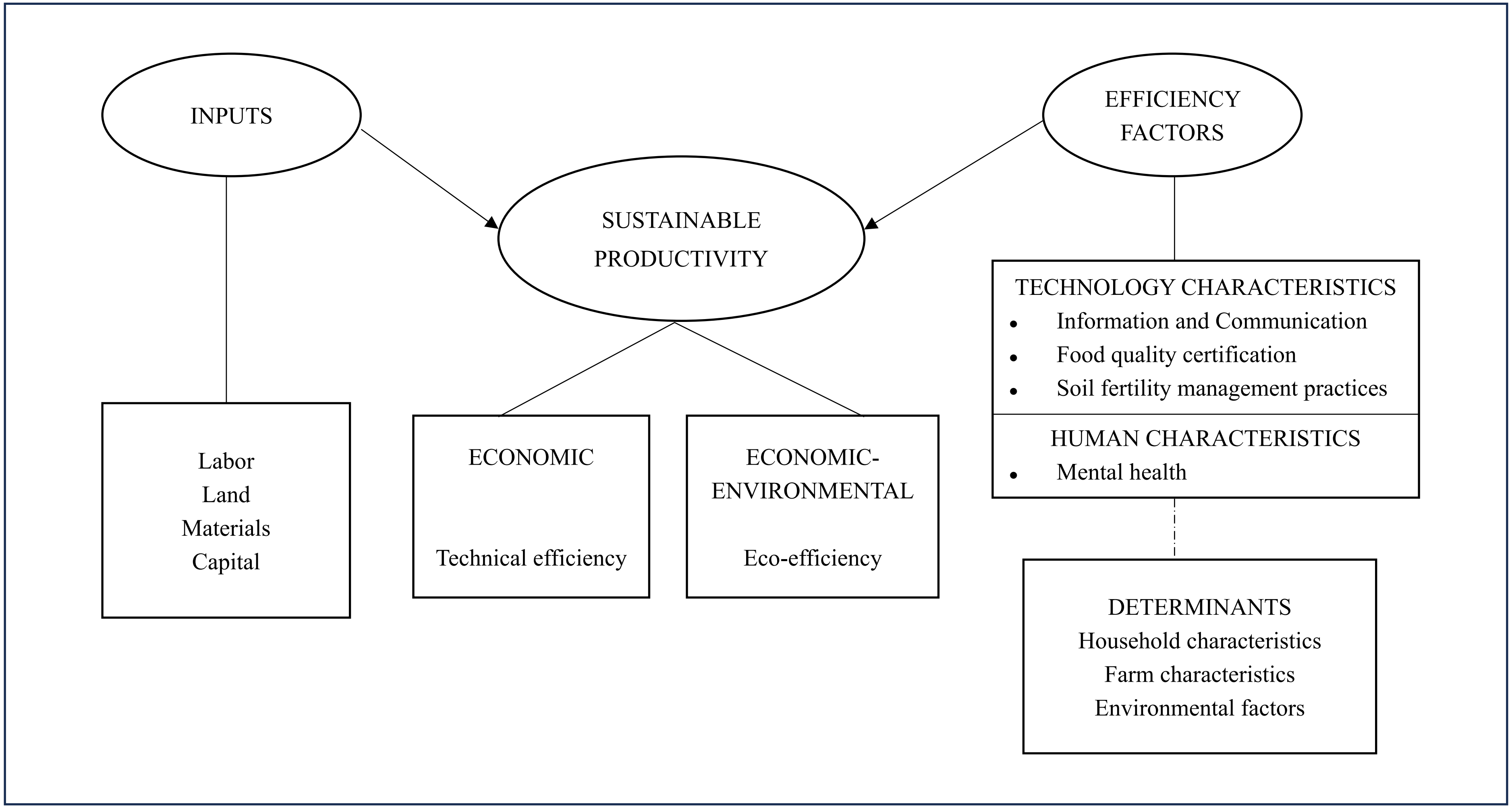

Figure 2-3 Illustration of the conceptual framework for this dissertation.

3. Methodology

For the empirical research work in the dissertation, various methods in the realm of productivity measurement and impact assessment are applied. Stochastic frontier analysis and its advanced models are useful for efficiency estimation and provide an empirical basis for the subsequent studies in the dissertation. The advanced models include the selection-corrected stochastic frontier model, which is applied to eliminate selection bias from unobservable factors in study 1, and the endogenous stochastic frontier model, which has the ability to effectively handle endogeneity issues in study 4. To understand farmers' choice of ICT use as well as the adoption of soil fertility management practices, this disseration adopts propensity score matching in study 1 and multivariate and ordered probit models in study 3, respectively. The endogenous switching regression model and three-stage least squares model are used to explore the causal effects of food quality certification adoption on eco-efficiency in study 2, and soil fertility management practices on fertilizer productivity in study 3.

3.1. Productivity and efficiency measurement

3.1.1 Stochastic frontier model

A variety of empirical techniques exist for estimating production frontiers and associated TE scores using observed production data, ranging from parametric (e.g., Stochastic Frontier Analysis) to non-parametric (e.g., Data Envelopment Analysis) approaches. One of the most widely applied methods is the stochastic frontier analysis (SFA), introduced by Aigner et al. (1977a) and Meeusen and van den Broeck (1977) and further developed by many other researchers. Kumbhakar and Lovell (2003) offered an extended review of stochastic frontier models. Unlike deterministic approaches, which attribute the difference between observed output and maximum attainable output solely to technical inefficiency, SFA recognizes the presence of statistical noise (e.g., random shocks outside producers' control, like weather) and is less sensitive to positive outliers. Consequently, SFA reformulates the production Equation (2-1) by introducing a producer-specific random shock term $\exp(v)$ and defining $\mathrm{TE} = \exp(-\mathrm{u})$ as

$$\mathrm{y} = f(x) * \exp(v - \mathrm{u}) \qquad (3-1)$$

This reformulated equation is commonly represented in logarithmic form by

$$lny = ln[f(x)] + v - u, \qquad u \geq 0 \qquad (3-2)$$

where v accounts for a two-sided error term in the estimation and u is a positive, one-sided error term accounting for technical inefficiency. Hence, in the stochastic frontier model, there is a composite error term ($\varepsilon = v - u$).

The stochastic frontier model is commonly estimated by maximum likelihood estimation and makes assumptions on the distribution of the two error terms u and v (Kumbhakar and Lovell, 2003). Usually, the noise term v is assumed to be normally distributed with zero mean and constant variance σ_v^2. The distributional of the inefficiency term u varies according to different assumptions but often follows a positive half-normal distribution with constant scale parameter σ_u^2:

$$v \sim iid(0, \sigma_v^2) \qquad (3-3)$$

$$u \sim iid(0, \sigma_u^2) \qquad (3-4)$$

Regarding the functional form for $f(x)$, common choices are the Cobb-Douglas (CD) and the translog functions (Coelli and Rao, 2005). The CD function has since been (and still is) widely used by economists because of its algebraic tractability and the advantages of providing a relatively good approximation of production processes (Reynés, 2019). But it has a limitation which is to impose an arbitrary level for substitution possibilities between inputs. The concept of the translog production function allows the transformation from a linear relationship between the output and considered production factors to a nonlinear one (Pavelescu, 2011). The approach is employed in studies 1, 2, and 4.

3.1.2 Selection-corrected stochastic frontier model

In the process of technology adoption, farmers face the choice of whether to adopt or not. This may lead to a problem of self-selection bias when analyzing the impact of technology adoption on farm performance. To be more specific, the problem is that if a correlation is observed between technology adoption and an outcome variable (such as output or efficiency), this could be attributed to the positive impact of technology. But there could also be a self-selection effect if farmers who are already more efficient than their peers are more likely to adopt the technology (Crost et al., 2007). Thus, the standard SFA techniques can result in biased and inconsistent estimators if the correlation between the unobservable factors affecting both the outcome and the selection process has not been considered.

To address selection bias, Heckman's sample selection model has been employed in regression studies for over four decades (Heckman, 1979). Building upon this framework, Greene (2010) introduced a selection-corrected stochastic frontier model, which incorporates sample selection corrected linear model into the normal-half normal stochastic frontier model by applying maximum simulated likelihood estimation. In recent years, a growing number of studies used the selection-corrected SFA to understand the nexus between farm sustainable productivity or efficiency and novel technologies or practices, such as internet use (Zheng et al., 2021), farmer groups (Abdul-Rahaman and Abdulai, 2018; Dong et al., 2019; Ma et al., 2018), advanced seed variety (Abdul-Rahaman et al., 2021; Villano et al., 2015), environmental friendly practices (Bravo-Ureta et al., 2012; Issahaku and Abdulai, 2020). In study 1, this method was adopted to analyze the impact of ICT use on farmers' technical efficiency.

Assume that unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier model; the combination of the stochastic frontier model with sample selection consists of two equations.

Sample selection:

$$D = 1\ [\boldsymbol{\alpha}' * \boldsymbol{z} + w > 0], w \sim N[0,1]$$

SFA model:

$$y = \boldsymbol{\beta}' * \boldsymbol{x} + \varepsilon, \varepsilon \sim N[0, \sigma_\varepsilon^2] \qquad (3-5)$$

Error structure:

$$\varepsilon = v - u$$

$$u = |\sigma_u U| = \sigma_u |U|\ where\ U \sim N[0,1]$$

$$v = \sigma_v U\ where\ V \sim N[0,1]$$

$$(w, v) \sim N_2[(0,1), (1, \rho\sigma_v, \sigma_v^2)]$$

In the above equations, D represents a binary variable: its value is 1 for the treatment group (technology adopters) and 0 for the control group (non-adopters). The variable y represents output, $\boldsymbol{z}$ is a vector of covariates included in the sample selection equation, and $\boldsymbol{x}$ is a vector of inputs in the production frontier. The parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the parameters to be estimated. The error structure $\varepsilon = v - u$ adheres to the typical characteristics of a stochastic frontier model. Importantly, the parameter ρ captures the presence or absence of selectivity bias.

3.1.3 Endogenous stochastic frontier model

As discussed in Section 3.1.1, the standard stochastic frontier model includes a deterministic part, a stochastic part for the two-sided error term, and a strictly non-negative inefficiency term. However, if the determinants of the frontier or the inefficiency term are correlated with the two-sided error term of the model, the results of the standard estimators will be affected by endogeneity. For example, when assessing the agricultural production efficiency of farms of different sizes, larger farms may achieve higher efficiency due to greater resource availability and a higher degree of specialization. However, farm size may also be correlated with the error term, as unobserved factors such as management quality or individual motivation can influence both farm size and efficiency. In such cases, endogeneity can compromise the reliability of the results.

Similar to the self-selection problem discussed before, several scholars have developed strategies in previous studies to deal with endogeneity issues and obtain unbiased results. Guan et al. (2009) proposed a two-step estimation methodology to handle the endogenous frontier regressors using the generalized method of moments. Kutlu (2010) addressed the endogeneity problem in the maximum likelihood estimation to solve the endogenous correlation between the regressors and the two-sided error term. Shee and Stefanou (2015) extended the methodology to overcome the endogeneity of the input bias problem within the stochastic frontier model to generate consistent estimates of the production parameters and technical efficiency. Karakaplan and Kutlu (2017) developed a model to handle endogeneity due to the determinants of the frontier, the inefficiency term, or both, which is the most advanced approach up to now.

There has been a notable increase in the number of studies applying Karakaplan and Kutlu's (2017) endogenous stochastic frontier analysis (ESFA) to explore the relationship between sustainable farm productivity and various efficiency factors, including internet use (Zhu et al., 2021), cooperative membership (Li et al., 2023; Neupane et al., 2022), off-farm income (Mondal et al., 2021), advanced seed variety (Ngango and Hong, 2021), agricultural innovations (Jerop et al., 2020). In study 4, this method was adopted to analyze the nexus between farmers' mental health and their efficiency.

Consider the following stochastic frontier model of Karakaplan and Kutlu (2017) with endogenous explanatory variables:

$$y = \boldsymbol{\alpha} * \boldsymbol{x}_y + v + u$$
$$x = \boldsymbol{\delta} * z + \epsilon \qquad (3-6)$$
$$u = h(\boldsymbol{x}_u \phi_u) * u^*$$

where y is the natural logarithm of the output; $\boldsymbol{x}_{\mathrm{y}}$ is a vector of exogenous and endogenous variables; x is a vector of all endogenous variables, and z is a vector of all exogenous variables; $\boldsymbol{x}_{\mathrm{u}}$ is a vector of exogenous and endogenous variables excluding the constant; $u \geq 0$ is a one-sided error term capturing the inefficiency; v and ϵ are two-sided error terms; u^* is a producer-specific random component independent from v and ϵ. Study 4 provides the application of this approach to measure the unbiased production parameters and technical efficiency of arable farmers in Section 4.4.

3.2. Technology adoption and its link to sustainable production

A traditional and intuitive approach to studying the nexus between technology adoption and sustainable production is to compare the difference in outcomes (i.e., treatment effects) between technology adopters and non-adopters. In this dissertation, the impact analysis is conducted by using propensity score matching (PSM), multinomial endogenous switching model (MESR), and multivariate probit models (MVP), respectively.

3.2.1 Propensity score matching

Considering the evaluation of the treatment effect of technology adoption, the decision of whether or not to adopt technology is a result of “self-selection”, and its decision is influenced by the resource endowment of the farmers themselves. Since the differing initial conditions between the treatment group ($D = 1$) and the control group ($D = 0$), we cannot observe the states of the treatment group if they had not adopted the technology and the control group if they had adopted it. Thus, the impact of technology adoption on farmers’ sustainable productivity cannot be determined through simple statistical comparisons. Therefore, a counterfactual framework needs to be constructed to deal with this type of “missing data” problem (Shadish et al., 2002). Propensity score matching (PSM) is an effective method to solve this problem (Rosenbaum and Rubin, 1983a).

Firstly, a probit regression is used to estimate individual’ propensity scores (P-score), which is defined as the conditional probability $p(\boldsymbol{z}_i)$ that an individual is predicted to be treated given observed characteristics $\boldsymbol{z}$. The propensity score is thus estimated as follows:

$$p(\boldsymbol{z}) \equiv p(D = 1|\mathbf{z}) \qquad (3-7)$$

Then, based on the calculated P-score, each treated individual is matched with a similar control individual. Propensity score matching includes a variety of matching algorithms, such as nearest neighbor matching, radius matching, kernel matching, etc. The most appropriate method for analysis is selected after evaluating the quality of different matching methods (i.e., how much selection bias is reduced).

After matching, the standardized bias (S) is used to check if the distribution of the relevant variables is balanced in both the control and treatment groups. After conditioning the propensity score, there should be no big differences between the covariates. The expression for S is:

$$S = \frac{|\bar{z}_{\text{treat}} - \bar{z}_{\text{control}}|}{\sqrt{\frac{s^2_{z,\text{treat}} - s^2_{z,\text{control}}}{2}}} \qquad (3-8)$$

where $\bar{z}_{\text{treat}}$, $\bar{z}_{\text{control}}$, $s^2_{z,\text{treat}}$ and $s^2_{z,\text{control}}$ represent the mean and variance of the covariate of both groups. Generally, the standardized bias should not exceed 10% (Rosenbaum and Rubin, 1983b).

PSM has been used in recent decades in the research of agricultural technology adoption to dive the groups and deal with self-selection bias from observable characteristics (Abebaw and Haile, 2013; Bravo-Ureta et al., 2021; Mendola, 2007; Nakano et al., 2018). In study 1, this method is adopted to analyze the impact of ICT use on farmers' technical efficiency.

3.2.2 Multinomial endogenous switching regression

When facing the issue of technology adoption, farmers may encounter complexities beyond simply choosing whether to adopt or not. For instance, there are five common types of irrigation systems, including drip irrigation, sprinkler irrigation, center-pivot irrigation, furrow irrigation, and terraced irrigation. Farmers not only have to think about whether to adopt irrigation but also have to make the decision about which technology to use based on their knowledge of soil, equipment, plant species, and land formation. Multinomial logistic regression is a technique used when the dependent variable is categorical, representing multiple choices for individuals (C = 1, 2, ..., J) and considers a vector of variables ($\boldsymbol{z}$) that determine the choice. Assume that the utility derived from individual choice j is represented as:

$$U_j = h(\boldsymbol{z} * \boldsymbol{\gamma_j} + \mu_j) \quad (3-9)$$

It is evident that an individual selects option j if and only if the utility derived from option j surpasses that of all other options. Therefore, the probability of an individual selecting option j can be expressed as:

$$P(C = j|z) = P(U_j \geq U_k, \forall k \neq j) = \frac{exp(\boldsymbol{z} * \boldsymbol{\gamma_j})}{\sum_{k=1}^{J} exp(\boldsymbol{z} * \boldsymbol{\gamma_k})} \quad (3-10)$$

After confirming the selection probabilities, further exploration of the relationship between technology adoption and performance requires impact analysis. Traditional modeling techniques, such as OLS (Ho et al., 2018; Martinsson and Hansson, 2021), Tobit models (Gómez-Limón et al., 2012), or a truncated regression model (Godoy-Durán et al., 2017; Picazo-Tadeo et al., 2012; Stępień et al., 2021), have one crucial assumption is that the explanatory variables and the error term are uncorrelated. However, in practical applications, as mentioned above, individuals may face a multinomial choice. The choice is not the result of random assignment and may be affected by unobservable factors such as management skills or motivation. Failure to meet this condition can lead to inconsistent estimates and inaccurate outcomes. To solve this endogeneity problem, a multinomial endogenous switching regression following Dubin and Mcfadden (1984) and Bourguignon et al. (2007) to correct for selection bias (DM model) is used.

This model aims at the consistent estimation of the relationship between the outcome variable and a set of exogenous variables $\boldsymbol{z}$. It also incorporates a selectivity correction term (λ_j), which is the estimated inverse mills ratios (IMR) computed using the predicted probabilities from Equation 3-10. The outcome equation for each possible regime j is given as:

$$\begin{cases} Regime\ 1: y_1 = \boldsymbol{z} * \boldsymbol{\beta_1} + \sigma_1 \hat{\lambda}_1 + \varepsilon_1 \quad if\ j = 1 \\ \quad \cdots \\ Regime\ J: y_J = \boldsymbol{z} * \boldsymbol{\beta_J} + \sigma_J \hat{\lambda}_J + \varepsilon_J \quad if\ j = J \end{cases} \quad (3-11)$$

where y_j is the outcome variable of the individual in regime j, $\boldsymbol{\beta_i}$ is a vector of the estimated coefficient of the factors influencing y, and ε_j is the error term.

Recent studies have adopted the MESR framework to examine the determinants and effects of technology adoption on farm productivity, taking into account selection bias in both observable and unobservable factors (Issahaku and Abdulai, 2020; Kassie et al., 2015; Khonje et al., 2018; Midingoyi et al., 2019; Tanko et al., 2023). In study 2, this method is adopted to analyze the impact of Chinese food quality certification, including three levels of hazard-free, green, and organic, on farmers' eco-efficiency.

3.2.3 Multivariate multiple regression model

So far, estimation has only been considered for single equations, but there are sometimes cases where multiple equations involving multiple technologies are employed simultaneously. For example, farmers' adoption of two sustainable agricultural technologies, straw return, and soil testing, are regarded as the two dependent variables. While the explanatory variables that affect the technology adoption in these two equations may differ, some unobservable factors may simultaneously influence the adoption of both technologies. Thus, the disturbance terms of these two equations should be correlated.

Considering correcting the correlation of the errors between multiple equations, jointly estimating these equations may have the potential to improve the estimation efficiency, which is named "system estimation". Sometimes, multiple equations are derived from the same maximization problem (e.g., from profit maximization issues for farms to investment and labor demand). Therefore, "cross-equation restrictions" exist theoretically. A multivariate multiple regression model provides a way to test these cross-equation restrictions.

The setup for the regression model is as follows. Suppose there are n equations (n explained variables - technologies), each equation with T observations, where $T > n$. In the i$^{\text{th}}$ equation, there are k explanatory variables. The i$^{\text{th}}$ equation can be written as:

$$\boldsymbol{y_i} = \boldsymbol{X_i}\boldsymbol{\beta_i} + \boldsymbol{\varepsilon_i} \quad (i = 1,2,\dots,n) \qquad (3-12)$$

Combining all the equations together yields:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & X_n \end{bmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} = X\beta + \varepsilon \qquad (3-13)$$

where $\boldsymbol{y_i}$ represents technology-i adoption: 1 for adoption and 0 for non-adoption, $\boldsymbol{\beta_i}$ is a vector of the estimated coefficient of the factors influencing $\boldsymbol{y_i}$ and $\boldsymbol{\varepsilon_i}$ is the error term.

The multivariate multiple regression approach models the association of a set of explanatory variables with each of the different technology adoptions simultaneously. It accounts for the potential correlation between unobserved disturbances and the relationship between different equations (Belderbos et al., 2004). Assume that regressors $\boldsymbol{X_i}$ are strictly exogeneous, the error variances are homoscedastic, and there is no autocorrelation within each equation.

The methods described are each applied to the four different empirical studies of this dissertation. More details on the methods applied can be found in the published versions of the empirical studies or the respective working papers.

Table 3-1 summarizes the context, methods, and main findings of the empirical studies.

Table 3-1 Overview of empirical studies in the dissertation and core findings

Study	Title	Research problem	Method	Core finding
Study 1	The impact of Information and Communication Technology on the technical efficiency of smallholder vegetable farms in Shandong of China	What factors influence vegetable farmers' adoption of Information and Communication Technology (ICT) in China? How does it impact Chinese farmers' technical efficiency?	Propensity score matching; Selection-corrected Stochastic frontier analysis	The difference in efficiency between ICT users and non-users is statistically and economically significant, which highlights the potential benefits brought by ICT use to smallholder farms in China.
Study 2	Does food quality certification improve eco-efficiency? Empirical evidence from Chinese vegetable production	What are the drivers for Chinese farmers' adopting different levels of food quality certifications? Do food quality certifications improve economic and environmental performance compared to conventional farms?	Stochastic frontier analysis; Multinomial endogenous switching regression	Certified farms are better than conventional farms in terms of combined economic and environmental performance. The eco-efficiency of farms increases with the improvement of food quality certification levels.
Study 3	Vegetable farmers' adoption of multiple soil fertility management practices in rural China	What is the adoption pattern of soil fertility management practices in China? How does the implementation of these practices affect farmers' fertilizer productivity?	Multivariate probit regression; Three-stage least squares model	There exists a complementary or substitutional relationship between the adoption of different SFMPs, considering multiple factors for vegetable farms. The intensity of SFMP adoption is found to be related to fertilizer productivity improvement.
Study 4	The nexus between mental health and efficiency of Chinese arable farmers	What demographic and environmental characteristics impact the mental health of farmers in China's arable production? How is mental health related to farmers' technical efficiency?	Principal component analysis; Endogenous stochastic frontier analysis	Healthier mental status is related to demographic characteristics (e.g., age, education, gender) and environmental characteristics (e.g., trust in neighbors, rural development). Mental health is an important driver for arable farmers' technical efficiency.

4. Summaries of empirical studies[1]

4.1 The impact of Information and Communication Technology on the technical efficiency of smallholder vegetable farms in Shandong of China

This study uses survey data from 763 vegetable farms in China to estimate the impact of farmers' ICT use on vegetable technical efficiency. China is the world's largest vegetable-growing country, as well as a major consumer and exporter of vegetables. As the most widely grown and economically important crop category in Chinese arable farming, vegetable production urgently needs to improve productivity. ICT has been confirmed in previous research as an important tool in enhancing farmers' production efficiency by helping them make better decisions to apply appropriate farming practices, providing information on products and markets, and improving communication between farmers and suppliers or customers. However, these studies ignored the self-selection bias, which is caused by the unobserved factor differences between adopters and non-adopters that are also relevant to their outcomes. In this study, propensity score matching and selection-corrected stochastic frontier models are combined to correct selection bias from both observed and unobserved factors. The study finds that ICT use has a positive impact on TE. Specifically, the average TE score of ICT users is 0.64, while ICT non-users have a lower score of 0.57. A quantile regression analysis further reveals a heterogeneous impact of ICT on TE: the less efficient farms have the largest effects. These results suggest that vegetable farmers' performance could be improved by the widespread use of ICT. Policy suggestions include increasing government subsidies to improve the penetration rate of ICT and further promote modernization in rural areas, as well as providing ICT-related training to improve farmers' information literacy in vegetable production.

[1] The full publications are not embedded in this dissertation to avoid copyright issues. However, the full versions were sent to the examiners for grading.

Publication:

Kang S., Ait Sidhoum A., Frick F., Sauer J., & Zheng S. (2023). The impact of information and communication technology on the technical efficiency of smallholder vegetable farms in Shandong of China. *Q Open*, 3(1), qoad017.

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Authors' contribution:

All authors contributed jointly to the development of the research question. Shijia Kang conducted the analysis and wrote the manuscript. Amer Ait Sidhoum and Fabian Frick contributed to reviewing and editing the manuscript. Data collection was supervised by Shaofeng Zheng. Johannes Sauer contributed to the conceptualization, reviewing of the manuscript, and supervision.

4.2 Does food quality certification improve eco-efficiency? Empirical evidence from Chinese vegetable production

This study applies survey data of 1855 vegetable growers in Shandong and Hebei provinces in China to examine the impact of food quality certification on vegetable farms' eco-efficiency. In 2001, to simultaneously enhance productivity and maintain environmental sustainability through changes in production behavior, the Chinese government proposed to develop a food quality certification system including three levels: "hazard-free", "green", and "organic" agricultural products. As a result, both economic and environmental benefits for farmers have been improved, as is found in previous literature. However, we are not aware of studies investigating food quality certification schemes under the topic of eco-efficiency in vegetable production. Vegetables are known to be energy sources for providing people with survival and nutrition, and they also have a great potential for economic and ecological improvement. Assessing the impact of food quality certification can provide valuable insights for policies on promoting sustainable agricultural production. Therefore, in this study, we follow a two-step approach: stochastic frontier analysis is applied to estimate eco-efficiency scores of smallholder farms, and a multinomial endogenous switching regression model is used to estimate the unbiased impact of different certifications on farms' eco-efficiency. According to the empirical results of this study, hazard-free certification increases the eco-efficiency score for vegetable farms by 2.7%, followed by green certification (4.6%) and organic certification (16.3%). Moreover, we find that farmers' decision to adopt food quality certification is significantly associated with farm size, farming experience, off-farm income, extension service, and social capital. Overall, the results suggest that vegetable quality certification can be a useful tool for improving farms' performance from both economic and environmental perspectives. Thus, policy interventions to promote the farmers' adoption of food quality certification should be considered to increase agricultural productivity and reduce environmental pressures. Local organizations such as cooperatives or rural extension services could be established to strengthen farmers' social networks and provide them with professional farming guidance. Certain financial subsidies for farmers should also be taken into consideration during the transition from conventional to sustainable production.

Publication:

Kang S., Frick F., Ait Sidhoum A., Sauer J., & Zheng S. (2023). Does food quality certification improve eco-efficiency? Empirical evidence from Chinese vegetable production. *Food Policy*, 121, 102564.

https://doi.org/10.1016/j.foodpol.2023.102564

Authors' contribution:

All authors contributed jointly to the development of the research question. Shijia Kang contributed to the conceptualization, methodology, formal analysis, and writing the original draft. Fabian Frick contributed to reviewing and editing the manuscript, as well as supervision. Amer Ait Sidhoum contributed to the conceptualization, reviewing, and editing of the manuscript. Data collection was supervised by Shaofeng Zheng. Johannes Sauer contributed to estimation strategies, reviewing the manuscript and supervision.

4.3 Vegetable farmers' adoption of multiple soil fertility management practices in rural China

This study uses farm survey data from 786 Chinese vegetable farms to analyze the factors that impact the probability and extent of farmers' adoption of multiple soil fertility management practices (SFMPs). Adopting SFMPs has become an important issue in developing economies, especially in tackling land degradation, erosion, and low soil fertility. Instead of roughly classifying farmers into SFMP adopters and non-adopters, we consider four SFMPs, including fertigation, subsoiling, straw returning, and soil testing, to offer detailed insights into the adoption pattern in rural China. In the first step, a multivariate probit model is applied to model farmers' adoption decisions and positive (complementary) or negative (substitutional) correlations between different SFMPs. We find that subsoiling has a positive correlation with both straw returning and soil testing while negatively correlated with fertigation. Besides, a negative adoption relationship is found between fertigation and straw return. The results of conditional probabilities of different SFMPs adoption confirm their relationships. In the second step, we adopt a three-stage least squares model and find that the probability and the intensity of farmers' adoption of SFMPs are associated with many factors, including the household head's gender, education, farm size, experience with natural disasters, tenure security, access to training, access to the internet, and social capital. What's more, farmers who adopt SFMPs are able to achieve higher productivity from their fertilizer use compared to those non-adopters. The results imply that policymakers should seek to promote local institutions and training providers to increase smallholder farmers' education and awareness of sustainable agricultural production, as well as strengthen social networks in order to improve the adoption of SFMPs.

Publication:

Kang S., Frick F., Zheng S., & Sauer J. Vegetable farmers' adoption of multiple soil fertility management practices in rural China. This manuscript was orally presented at the 97th Agricultural Economics Society (AES) conference and is currently under peer review.

Authors' contributions:

All authors contributed jointly to the development of the research question. Shijia Kang conducted the analysis and wrote the manuscript. Fabian Frick contributed to reviewing and editing the manuscript. Data collection was supervised by Shaofeng Zheng. Johannes Sauer contributed to conceptualization and supervision.

4.4 The nexus between mental health and efficiency of Chinese arable farmers

This study uses a 3-year panel dataset of 1550 arable farmers in China to estimate the predictors of mental health and the nexus between farmers' mental health and their efficiency. Recent studies explored the effects of mental health in various economic aspects, but the potential of mental health to improve efficiency during production, especially in the agricultural sector, has rarely been specifically discussed. Thus, this research aims to reveal the factors that affect farmers' mental health and explain the effect of mental health on technical efficiency in arable farm production. In the first step, we employ a principal-component factor analysis to obtain factor scores of farmers' mental health. The aim is to identify latent factors that explain the correlations among observed variables, thereby enhancing the validity of the mental health measurement. In the second step, an endogenous stochastic frontier model is applied to explore the relationship between mental health and farmers' technical efficiency, considering the potential endogeneity problem. Our results suggest that female household head, householder members' illness, and low income have a significant negative association with the probability of farmers' mental health, while the level of trust in surrounding communities, education level, age of household head, access to training, and rural development do well to mental health. What's more, a significant and positive relationship is found between mental health and technical efficiency for Chinese arable farmers. In the third step, this study undertakes a further analysis of the heterogeneous effect of mental health on farm efficiency, considering several demographic and farm characteristics. We find that mental health has a greater impact on efficiency among higher-educated farmers and those who are involved in off-farm activities. Based on the results, policy recommendations include improving farmers' mental health by expanding health insurance coverage, fostering the development of rural areas, and improving farmers' educational levels and social connections.

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5. Discussion and conclusions

This dissertation aims to examine the drivers for sustainable production of arable farms in China. In the four studies, I assess the adoption of ICT, food quality certification, soil fertility management practices, and farmers' mental health, as well as their links to farm performance. Specifically, studies 1 and 4 focus on the economic perspective, while studies 2 and 3 expanded this perspective further to also take the environmental perspective into consideration. In this section, I discuss the findings of the four individual studies, potential limitations, future research avenues, and related policy implications.

5.1 Discussion of the empirical studies

5.1.1 The impact of Information and Communication Technology on the technical efficiency of smallholder vegetable farms in Shandong of China

In study 1, we estimate and compared the TE scores for ICT users and non-users: the mean TE score for ICT users is 0.62, while the mean TE score for ICT non-users is 0.57. If we control for unobservable bias, the TE score for ICT non-users increases by 0.03, and the TE score for ICT users increases by 0.01. After considering both observable and unobservable bias, the difference in mean TE between ICT users and non-users increases to 0.07. This indicates that neglecting the endogeneity problem in the analysis can lead to an underestimation of the mean TE difference between ICT users and non-users. This finding is consistent with previous studies by Zheng et al. (2021) and Zhu et al. (2021). The results also illustrate the positive effect of ICT use on vegetable farmers' TE, confirming the significance of technology adoption on sustainable agricultural production. In addition, there is heterogeneity in the impact of ICT on TE: less efficient farms are most affected; the impact becomes smaller as TE increases, and the most efficient farms experience a statistically insignificant impact.

However, compared to neighboring countries that produce vegetable producers, such as Vietnam (Nguyen et al., 2021) and India (Murthy et al., 2009), Chinese vegetable farmers seem to have lower TE scores. A possible explanation for this gap could be that the restrictions on land use or transfer in China limit the ability of producers to invest in land resources and improve their technical efficiency

(Krusekopf, 2002). In addition, as the world's largest producer and consumer of vegetables, China faces serious environmental challenges such as soil pollution and water scarcity (Khan et al., 2009), making it difficult for vegetable farmers to produce in an efficient way.

The factors affecting farmers' ICT adoption are also discussed: male and young farmers are more likely to apply ICT than female and old farmers. Farmers' experience, cooperative participation, information literacy, and proximity to government have significant positive impacts on ICT use, as these factors can contribute to the fact that farmers are more likely to access information about agricultural production.

5.1.2 Does food quality certification improve eco-efficiency? Empirical evidence from Chinese vegetable production

In study 2, we analyze the impact of three levels of food quality certification (hazard-free, green, and organic) on farm eco-efficiency in China. Our empirical application focuses on the eco-efficiency of conventional farms in vegetable production compared to farms in the three different levels of certification systems. Based on the results of our study, we find that the eco-efficiency of most farms was distributed between 0.3 and 0.7. To be specific, the average eco-efficiency of conventional farmers is 0.46, which is the lowest. For certified vegetables, organic farmers have the highest average eco-efficiency score of 0.62, followed by green and hazard-free farmers, which are 0.50 and 0.48, respectively. The results imply that food quality certification is associated with higher levels of eco-efficiency, which is consistent with the research in New Zealand (Müller et al. 2015) and Vietnam (Ho et al. 2018).

Compared to conventional farms, farms adopting food quality certification have significant expenditure reductions in utilities, pesticides, plastics, and fertilizer. In this sense, food quality certification has the potential to enable farmers to switch from conventional to more sustainable production practices, which can generate significant environmental benefits without compromising economic productivity. The result is consistent with the findings of an earlier study by Godoy-Durán et al. (2017) on horticultural farms in southeastern Spain.

The factors influencing farmers' adoption of different certifications are also explored in study 2. Experienced farmers or those who have larger farms prefer to adopt hazard-free and green certifications.

The reasons may be that experienced farmers have more knowledge and practice accumulation and pay more attention to environmental quality and long-term impacts (Hoque et al., 2022). For larger farms, the fixed costs associated with certification can be shared due to scale effects, thus reducing the adoption costs for farmers. However, organic farming is associated with smaller-sized farms and higher labor costs, possibly because of the higher share of hired labor (Uematsu and Mishra, 2012) required by strict constraints on organic farming in vegetable production (Hanson et al., 2004). Easy access to rural services (e.g., agricultural cooperatives), as well as social capital (e.g., trust, frequency, and reciprocity of social networks), increases the likelihood that farmers produce certified vegetables, which supports the fact that membership in farmers' associations, as well as social ties, play an important role as a source of information on agricultural innovations adoption (Mutenje et al., 2016; Rahman and Yamao, 2007). What's more, off-farm income has a negative impact on farmers' adoption of food quality certification. More time spent on sustainable production may lead to less time for off-farm activities, which results in lower off-farm income. Farmers with substantial off-farm income may be less willing to make this trade-off.

5.1.3 Vegetable farmers' adoption of multiple soil fertility management practices in rural China

In study 3, we explore the interrelationships between farmers' adoption of SFMPs, including subsoiling, straw return, soil testing, and fertigation in vegetable production. Substitution relationships are those in which the adoption of one practice may reduce the likelihood of adopting others. Specifically, the probability of adopting fertigation alone is higher than the probability of combining it with the other three practices. This substitution relationship may be based on the vegetable farmer's consideration of cost-effectiveness as a rational producer in choosing SFMPs (Paris, 2002), the complexity of the practices, the ease of adoption (Levidow et al., 2014), and some environmental factors (e.g., land tenure and greenhouse equipment). Complementary relationships occur in the simultaneous adoption of different practices, such as the adoption combinations of subsoiling with the other two practices of straw return and soil testing. This can be attributed to their functional synergies, optimization of resource use, the combined effects they bring to soil biology and physics, and the practical experience and knowledge of farmers (Teklewold et al., 2013).

Farmers' behavior of adopting SFMPs varies due to several factors. With respect to household characteristics, female farmers are more likely to implement SFMPs, highlighting important gender differences in agricultural technology adoption decisions in developing countries. High education levels, internet access, social capital, and training assistance can lead to more sources of information (e.g., professional equipment or technical knowledge) and proved to be positively related to SFMPs adoption (Ma and Wang, 2020).

In terms of farm characteristics, large farms are more likely to be involved in SFMPs investment. This may be because they can take advantage of economies of scale and can better adapt to production technology needs (Amsalu and de Graaff, 2007). Some other vegetable production techniques, such as greenhouse cultivation or intercropping, could be combined with some specific SFMPs to enhance soil health and overall farm productivity (Yin et al., 2020). Among the environmental factors, land tenure and experience of losses due to natural disasters have positive impacts on SFMPs adoption. Land tenure provides farmers with secure, long-term tenure rights to the land they work on, which helps them take a long-term view of soil health and fertility, including investing in SFMPs. Farmers who have suffered disaster losses have a higher level of risk awareness and are more capable of integrating a trade-off analysis of economic benefits and adoption costs into their decision-making processes for adopting SFMPs (Martey and Kuwornu, 2021).

5.1.4 The nexus between mental health and efficiency of Chinese arable farmers

In study 4, we aim to fill a research gap by exploring farmers' mental health and the underlying effect of mental health on farm efficiency. Given the inherent challenges of directly measuring farmers' mental health as a latent variable, we employ principal component factor analysis to create factor scores based on the ability to capture the latent constructs behind the observed variables, thereby improving the validity of mental health measures.

The results for the determinants of farmers' mental health in the first stage of the endogenous stochastic frontier model show that women are more likely to be depressed than men (Albert, 2015; Booth and Lloyd, 2000). We also find that if some household members are seriously ill or the household has low incomes, the farmers are more likely to be mentally unhealthy (Kim, 2017; Münster et al., 2009). Similar to the findings of Rudolphi et al. (2020), younger farmers may be subject to more stressors than older farmers. Better education is also an important risk predictor of mental health (Brennan et al., 2022; Zhu et al., 2022). For the environmental factors, farmers who trust their neighbors tend to show better mental health scores, and rural development and training programs have the potential to improve farmers' mental health state (Abunyewah et al., 2024; Ginexi et al., 2000; Liang et al., 2022; Palmer and Strong, 2022; Wang and Zhu, 2023).

According to the results for the second stage of the endogenous stochastic frontier model, after addressing the endogeneity issue, the effect of mental health on farm efficiency has increased from 0.20 to 0.37. This suggests that there is a positive relationship between mental health and farm production efficiency. Moreover, if the endogeneity is ignored in the analysis, we will not only have a biased conclusion but also underestimate the effect of mental health on Chinese arable farm production.

As a further step, we explore the heterogenous effect of mental health based on several demographic and farm characteristics, including age, gender, level of education of the household head, farm size, and off-farm employment. The interaction coefficient between depression and high education is positive, indicating that good mental health may have a positive effect on efficiency in households with higher education. This may be because farmers with higher education have better stress management skills and coping strategies, enabling them to reduce the adverse effects of depression (Zhu et al., 2022). However, considering possible reasons such as financial stress and additional pressure to balance agricultural and non-agricultural responsibilities, depression has a negative impact on the efficiency of households involved in off-farm activities (Logstein, 2016).

5.2 Limitations and recommendations for future research

This dissertation has five main limitations. Future studies should focus more on expanding the scope of individual studies to increase the validity and presentiveness of the empirical findings and policy implications. In studies 1 to 3, due to limited funds and time, our survey samples are limited to cross-sectional datasets from two large vegetable-growing provinces in China. Although the data selected provide a representative reflection of vegetable production in major provinces, there may be a sample targeting bias if the results of the study are extended to the whole country. Therefore, future research should expand the study area and sample size to compare and analyze vegetable production and efficiency across different regions. This would offer deeper insights into how varying natural conditions, demographic characteristics, and other factors influence the sustainable production of vegetable growers. Additionally, the use of panel data in future studies would enable a more rigorous treatment of endogeneity by accounting for time-invariant unobserved factors. It would also provide a more comprehensive understanding of the drivers of sustainable production in arable farming. Panel data, on the one hand, facilitate the dynamic analysis of technological adoption and, on the other hand, allow for a better assessment of its impact on farms' sustainable performance.

In study 1, as a future outlook, new ICT developments might bring about new implications for farm performance. The Central Government of China proposed to accelerate the planning and construction of the fifth-generation communication technology (5G) in rural areas, establish the agricultural big data system, and promote the in-depth integration of new-generation information technology with agricultural production. Therefore, the advent of the 5G era is not only a new opportunity for agricultural development but also a new chapter to study innovative drivers of farm sustainable productivity.

In Study 2, one of the criticisms of the eco-efficiency approach is that it ignored fundamental elements of sustainability (e.g., planetary boundaries), i.e., it focused on the relative level of environmental pressure rather than the absolute level (Martinsson and Hansson, 2021). This means that even the smallest pressure in the sample at hand may exceed the maximum possible pressure. Some studies incorporate planetary constraints in their eco-efficiency analysis, such as Usman et al. (2023), which considers many interrelated environmental variables, including climate change, biodiversity loss, natural resource extraction, etc. Future research should further include a comprehensive set of environmental pressures when measuring eco-efficiency. Particular attention should be paid to sustainability considerations, such as information on the maximum allowable pollution levels on each farm.

In study 3, although an effective analytical framework is applied to assess the patterns of SFMP adoption, the predictors of adoption, and the impact of SFMP adoption on fertilizer productivity, analyses are limited by the currently available data. Over a longer period of time, technology adoption behavior does not only include initial adoption. It also includes continued adoption and the intermediate stage between the two. This includes cases where initial adoption does not lead to continued adoption after a period, as well as the reasons behind sustained adoption and abandonment. Thus, future research could explore the key factors influencing multiple SFMP adoption through a dynamic developmental perspective by tracking farmers' surveys. Specifically, identify and differentiate the performance of technology adoption behavior at different stages and under different circumstances to seek feasible paths and policy recommendations to promote the technology adoption for sustainable production.

In Study 4, although we use a standardized depression scale, other objective measures of mental health could provide a robustness check on its impact on agricultural productivity. Furthermore, mental health in agriculture is a challenge that requires as much research and policy attention as other long-standing occupational health and safety issues. We hope that this study will inspire further action to increase interest in farmers’ mental health and further research on how to support farmers and other farm workers, thereby advancing the sustainability of agriculture.

5.3 Policy recommendations

The overall aim of this dissertation is to explore the drivers for sustainable production of Chinese arable farms, particularly considering the adoption of information and communication technology, food quality certification, soil fertility management practices, and farmers’ mental health.

In terms of ICT adoption, first, our findings indicate the benefits of ICT use to improve TE in the sector, which suggests that the government should improve the penetration rate of ICT. For example, it can increase relevant subsidies and promote the modernization of rural areas, especially the investment in broadband infrastructure. Second, ICT use appears to be particularly effective for low-TE farms, indicating that those farms should be paid more attention. Third, results from the propensity score model suggest that effective ways to foster ICT adoption are the provision of training and enhancing information literacy in general. Thus, the government should encourage and guide farmers to use ICT to obtain agricultural information by providing ICT-related training and improving their information awareness and literacy. Especially for less technically efficient and less educated farmers, their level of use of ICT should be improved so that they can access and apply fundamental information and benefit from it. Fourth, the department of agricultural information services should provide effective guidance and regulation, which will lead to an optimal match between information supply and demand, thereby facilitating farmers to obtain information resources via ICT.

There are several policy implications for the promotion of food quality certification to enhance agricultural productivity and ease environmental burdens. First, based on the finding that certification schemes improve eco-efficiency, policymakers should promote farmer participation in quality certification schemes given the evidence indicating their positive impact on eco-efficiency. This might involve offering farmers training, financial aid, and technical assistance. For instance, local institutes such as cooperative organizations or rural extension services could be established to strengthen farmers' social networks and provide them with farming guidance to share experiences, resources, and technologies. Second, based on our research findings on the determinants of certification adoption, agricultural policies should focus on these relationships. For example, farm size is found to be an important predictor of certification adoption, but it has different directions of influence for different certification levels. Further research and policy initiatives could focus on the reasons behind this and try to find adoption incentives adapted to farms of different sizes. Ongoing evaluations of the current food quality certification schemes are essential to ensure that they match the specific needs and characteristics of the farmers. Third, switching from conventional to certified farming may bring a short-term financial burden, which may lower farmers' willingness to participate. Therefore, policymakers should consider boosting farmers' motivation to participate in certified farm production by offering certain financial subsidies for growers during the transition. Furthermore, farmers' access to input markets has shown to be an important adoption predictor, possibly because non-conventional inputs (i.e., environmentally friendly inputs, such as organic fertilizers and low-toxicity pesticides) are less available in more remote locations. Hence, price support for farmers to purchase these materials could be considered.

Concerning the adoption of SFMPs, several policy recommendations are put forward based on the results. Firstly, developing educational programs is suggested to be conducted by professional agricultural experts and provide farmers with information about SFMPs that are adapted to the needs of different farms. In addition, training should be provided to farmers on SFMPs and their benefits, and the exchange of knowledge and experience between farmers and agricultural extension services or researchers should be eased to raise their awareness of sustainable agricultural production. What is more, local farmers' organizations such as cooperatives should be encouraged and promoted to increase smallholder farmers' access to resources and markets and effectively handle soil fertility. Lastly, the government should offer financial subsidies and incentives to smallholder farmers to encourage them to adopt SFMPs without compromising the adoption of other practices beneficial for the environment.

In the context of improving farmers' mental health, policymakers should first prioritize efforts to improve access to healthcare services in rural areas, including medical assessment and infrastructure, to lower the rate of both physical and mental illness. Secondly, Enhancing farmers' social capital and building trust networks in rural communities are also recommended. Strong social networks can strengthen mutual support among farmers. For example, when they encounter problems in production or life, they can get care and support from their surroundings, thereby reducing the risk of depression. In addition, extension education programs can help farmers themselves master the knowledge and skills needed to effectively solve mental health problems. Thirdly, policies such as providing psychological counseling should also focus on improving the mental health of arable farmers who have off-farm employment. These farmers not only need to be involved in agricultural activities but also need to spend extra time and energy on non-agricultural activities.

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