Agricultural Mechanization Services, Adverse Selection and By-Stage Productivity of Small Farms: Evidence from Wheat Production in Northern China

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Abstract

Abstract The rapid expansion of mechanization services has revolutionized agricultural production in developing countries, where small farms dominate. However, the impact of these services on the productivity of small farms across multiple production stages is not well understood. We investigate the adoption of mechanization services at different stages and assess their productivity effects, both at each stage and overall. Utilizing a balanced panel of 145 wheat farms in Northern China, with data from three waves of farm surveys from 2013 to 2020 matched with NDVI crop indices, we provide comprehensive insights into inputs and outputs at each stage, allowing for the estimation of a multiple-stage production function. We find that mechanization services are underutilized in the plant protection stage, where performance is less observable. This underutilization, linked to other production stages, hampers capital deepening and productivity at the farm level, offering insights into farms' by-stage adoption of mechanization services and overall productivity.

Keywords: By-stage Production Function, Mechanization Service, Agricultural TFP

JEL Codes: O11; D33

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1 Introduction

Enhancing the productivity of small farms through the provision of appropriate equipment is crucial for addressing food security and rural poverty issues in developing countries. Globally, there are approximately 475 million farms, accounting for 84% of the estimated 570 million, which are smaller than two hectares relying on the labor intensive technology for production (Abraham et al., 2022; Gomez-Zavaglia et al., 2020; Ackerberg et al., 2015). More than 80% of these farms are located in developing countries across Asia, Africa and Latin America. Despite occupying only 12% of the world's agricultural land, small farms employ over two billion individuals in rural areas and contribute to 80% of the food production in major developing countries. Moreover, these farms also host a significant proportion of the world's poorest and most food-insecure populations (Lowder et al., 2016). While various factors, such as geography, agro-climatic conditions, limited economies of scale, risk tolerance and limited access to credit, quality inputs and technology, influence productivity, they pale in comparison to the profound impact of inadequate mechanization levels and the absence of access to quality capital equipment on the potential productivity enhancement of small farms. Consequently, there is an urgent need for innovative technological and institutional solutions to enhance mechanization levels within small-scale farming systems.

In recent two decades, a widely utilization of agricultural mechanization services has substantially improved the mechanization level and productivity of small farms in many Asian and African developing countries (Zhang et al., 2015; Diao et al., 2020; Daum et al., 2021; Caunedo et al., 2022). On one hand, agricultural mechanization services enable small farms to conduct the ploughing and harvesting activities more efficiently, granting them access to power-intensive tractors and harvesters that would otherwise be unaffordable. On the other hand, agricultural mechanization services also facilitate the adoption of newly developed advanced technologies, including GPS-based seedling, traffic-control harvesting and other standardized farming practices, which are integrated into capital equipment. This transformation has also been supported by government subsidies and tax incentives, contributing to address the challenge of insufficient self-owned capital in agriculture of developing countries. Taking China as an example, where only 15% of farms possessed machinery and equipment valued up to RMB 150,000 yuan, the comprehensive mechanization ratio had reached 72% by 2021.[1] A similar trend of rapid growth in agricultural mechanization services has also been observed in other developing countries across Asia and Africa.[2]

Despite the growing importance of mechanization services in developing countries' agriculture,

[1]For example, average mechanization service ratios for the ploughing, seeding, and harvesting stages of production for rice, wheat, and maize in China have reached 86%, 60%, and 65 % respectively (MARA, 2022).

[2]In Asia, a remarkable 72% of farms have access to mechanisation services in Bangladesh and a large proportion of farmers got access to mechanisation services for harvesting activities in India (Fuad and Flora, 2019). In Latin American and African countries, similar pattern also applies. For example, there are up to 80 % of farms utilizing machinery services in Ghana (Cossar, 2019); markets for combine-harvesting of wheat have emerged, and even small farms make use of these services in Ethiopia (Fisseha et al., 2017).

there are emerging challenges that restrict their further development. One major challenge is that the tendency of small farmer users to under-utilize mechanization services in specific stages of agricultural production, which can have negative impact on farm-level productivity. Unlike manufacturing production, agriculture involves a series of interconnected activities throughout the entire production process, with the outcomes of earlier stages only becoming apparent after the harvest. Without the ability to effectively monitor the performance of service providers in earlier stage of production, small farm users often need to reduce costs by opting for the cheapest service providers and packages for particular stages of production. Additionally, the loss in inefficiencies of earlier stages due to the under-utilization of mechanization services can also impact subsequent stages, leading to negative spill-over effects in subsequent stages. As a consequence, the optimal choice of using mechanization services by stage may not align with optimal choice of mechanisation service at the farm level. Addressing this challenge requires analyzing how small farms configure their mechanization services at different stages of production and assessing their impacts on productivity.

In this paper, we investigate the adoption of mechanization services by small farms and their impact on both stage-specific and overall farm-level productivity. Our objective is to gain a deeper understanding of whether the by-stage selection of service providers and packages is optimal for enhancing productivity of small-farm users. To achieve this goal, we develop a three-stage production function that takes into account the varying complexities of tasks, risks, and adverse selection associated with different stages of production. Using this framework, we analyze small farms' decisions regarding the utilization of capital, labor, and mechanisation services in different production stages. To empirically estimate the three-stage production function in the context of wheat production, we use small wheat farms in Northern China as a case study.

China, as a global leader in wheat production, accounted for the largest total wheat sowing area and production in 2021, with 23.57 million hectares and 136.9 million tons, respectively, representing 10.59% and 17.6% of the global total. Notably, a significant portion of China's wheat production comes from Northern China, with Henan and Shandong alone contributing to 41.09% of the total production. The majority of wheat producers in Northern China are small farms, with over 85% operating on plots totaling less than 0.67 hectares (or 10mu), and an additional 10% operating on plots totaling less than 2 hectares (or 30 mu). Over the past decade, mechanization services in Northern China have experienced rapid expansion, leading to substantial improvement in the mechanization levels and productivity of small wheat farms. While the overall mechanization ratio in wheat production has exceeded 97% due to this expansion, disparities in mechanization levels and the utilization of mechanization services remain large across different stages of wheat production.

Using a unique dataset obtained from three-period tracing farm surveys that collect detailed input and output information for each stage of production, combined with satellite monitoring of crop growing indices, we estimate a multiple-stage production function that encompasses the three stages of wheat production (namely, ploughing/seedling, plant protection, and harvesting) for 145 farms in Northern China. By estimating the productivity for each stage, we analyze the impact of mechanization services on stage-specific productivity by examining the utilization of capital, labor, and mechanization services by wheat farms. Additionally, we also aggregate the productivity estimates for each stage to measure farm-level productivity using Domar weights proposed by Brandt et al. (2022). We then compare these estimates with those obtained from the farm-level production function estimates. The richness of our dataset enables us to not only assess the aggregate productivity of wheat farms but, more importantly, to examine variations in farm-level performance across different stages of production, where varying levels of mechanization services are employed. This provides valuable insights for better understanding how mechanization services influence farm-level productivity within the context of a complex and interdependent farming operation.

We find that wheat farms in Northern China have experienced a significant growth of productivity, at the rate of 1.5% a year over the past decade, with mechanization services contributing to approximately half of this growth. However, the productivity of the plant protection stage, which involves the use of relatively fewer machinery and equipment (as well as fewer mechanization services), is considerably lower compared to the ploughing/seedling and harvesting stages. This discrepancy poses an emerging challenge to further enhancing farm-level productivity. While mechanization services have proven effective in improving the mechanization levels and productivity of the ploughing/seedling and harvesting stages, their impact on the productivity of the plant protection stage for wheat farms is limited. This is partly attributed to that small farm users can not effectively monitor the performance of service providers in the plant protection stage, since the outputs of the stage are not directly observable. Consequently, they adversely select to minimize the utilization of mechanization services in this stage, which in turn negative affect its by-stage productivity and generate negative spillover effects on downstream-stage productivity. Our findings help explain why small wheat farms are hesitant to rely more heavily on mechanization services to replace their self-owned capital and labor, especially in the plant protection stage, compared to the ploughing/seedling and harvesting stages. Additionally, our study also sheds light on the behavior of wheat farms in Northern China as they scale up their operations. As farms expand their scale, they are more inclined to acquire their own machinery and equipment to be utilized across all stages of wheat production. This helps mitigate the negative cross-stage spillover effects.

To the best of our knowledge, this paper makes two significant contributions to the existing literature. Firstly, it represents the first attempt to examine the impact of mechanization services on the productivity of small farms by conducting estimations of the multiple-stage production function. Drawing upon the frameworks developed by Ortiz-Bobea (2013) and Brandt et al. (2022), we estimate the productivity of small farms at each stage and establish a linkage between agricultural productivity and the utilization of mechanization services. This innovative approach incorporates the interaction between different stages of agricultural production into the analysis of mechanization services' impact on farm-level productivity. Secondly, we highlight the emerging challenge of independently selecting service providers and packages for the plant protection stage of agricultural production, in which the output performance of mechanization service providers is not directly observable. We demonstrate that this practice has a negative effect on the use of mechanisation services and the productivity of the plant protection stage, as well as the overall productivity performance of mechanization services at the farm level (when there are negative spillover effects passed on to the downstream production stages). Failure to adequately address this issue significantly restricts the potential role of mechanization services in enhancing the productivity of small farms, highlighting the importance of further attention to this matter.

Our research is aligned with three other distinct bodies of literature. The first body of literature examines the impact of mechanized services on farm performance, as explored by Yang et al. (2013), Diao et al. (2020), Zhang et al. (2017), and Paudel et al. (2019). For example, Yang et al. (2013) studied the seasonal migration of combine harvesters across different provinces in China and its contribution to agricultural productivity growth. Similarly, Paudel et al. (2019) found that moderate mechanization, such as the use of mini-tillers, significantly increased rice yields for smallholders in Nepal's hilly regions. However, these studies do not explain why mechanization services are more effective in promoting agricultural productivity growth in certain countries and regions compared to others. The second body of literature focuses on analyzing the role of market development in influencing the adoption of mechanized services, as demonstrated by Daum et al. (2021), Caunedo et al. (2022), and Foster and Rosenzweig (2022). For example, Foster and Rosenzweig (2022) discovered that the high transaction costs between service providers and users could reduce the efficiency and quality of the service market. Adu-Baffour et al. (2019), Daum and Birner (2017), and Daum and Birner (2020) highlight the importance of addressing institutional, financial, and training issues related to the service-providing market to facilitate the adoption of mechanization services, rather than solely relying on government subsidies. However, these studies do not elucidate why mechanization services are more likely to be adopted at specific stages of farm production, such as tilling, sowing, and harvesting. The third branch of the literature concentrates on estimating the by-stage production function, as explored by Antle et al. (1994), Behrman et al. (1997), Ortiz-Bobea (2013), and Brandt et al. (2022). These studies have developed and applied the multiple-stage production function approach to assess the productivity of different stages in manufacturing production. However, they do not specifically examine the interaction between mechanization services and stage-specific productivity in agriculture. By incorporating these three bodies of literature, our research adds to the existing knowledge by not only investigating the impact of mechanization services on farm performance but also exploring the factors influencing their effectiveness and adoption at different stage of production.

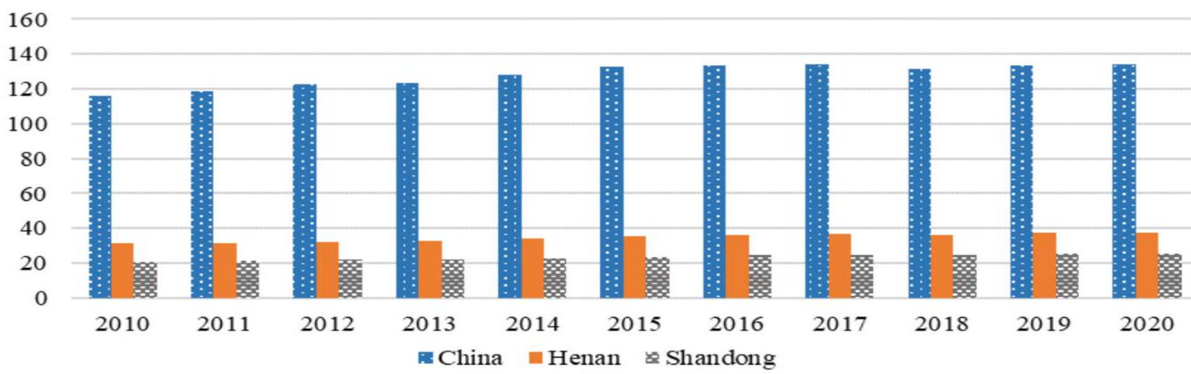
The remainder of the paper is structured as follows. Section 2 presents background information regarding wheat production by small farms in Northern China, as well as the impact of mechanization services on wheat production over the past decade. In Section 3, we detail the panel data sourced from three waves of random-sampling/tracing farm surveys conducted in 2014, 2016, and 2021. This dataset comprises comprehensive input and output information categorized by stages of production. We also provide an overview of the major variables to be employed in estimating the by-stage production function. Section 4 outlines the empirical methodology to estimate the multiple-stage production function and the empirical strategies we will employ to investigate the effects of capital deepening and mechanization services on both by-stage productivity and aggregate farm-level productivity. In Section 5, we present the empirical findings, followed by a series of robustness checks conducted in Section 6. Finally, Section 8 presents the conclusions drawn from our analysis.

2 Wheat Production in Northern China and the Role of Mechanization Services

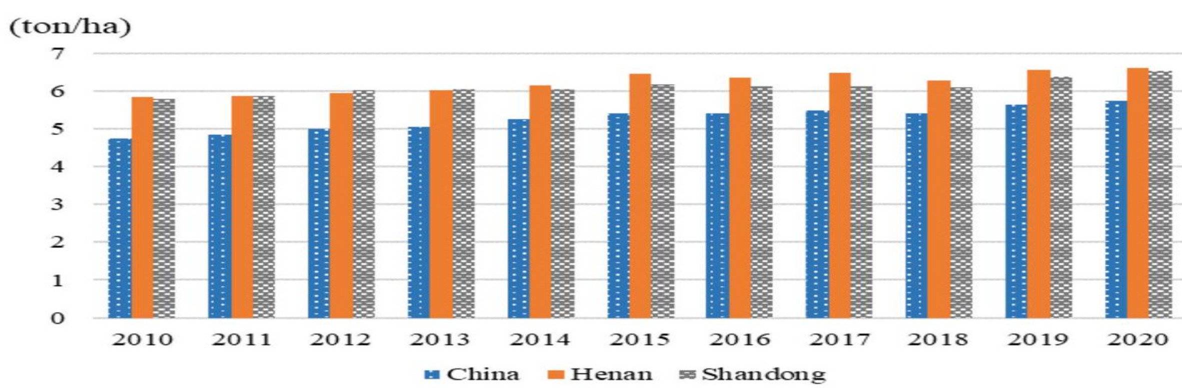
Wheat is one of the three most important grain crops in China, second only to rice. It is primarily consumed within the country and boasts a rich cultivation history spanning over the past five thousand years. As a winter crop, wheat thrives mainly in the Northern provinces, where temperatures can plummet to negative double digits during the winter season. It typically alternates with other dry-land crops like maize or oil seeds. In 2022, China's wheat production reached a record high of 137.7 million tons, accounting for 30% of the global total. This achievement has consistently positioned China as the world's largest wheat producer for the past two decades. Out of all the wheat production regions in China, over 79% of wheat production originated from five provinces in North and Middle China, including Henan, Shandong, Hebei, Anhui, and Jiangsu. Henan and Shandong alone accounted for nearly half of the overall production. In these regions, wheat cultivation is primarily carried out by small farms. In 2021, more than 85% of wheat farms in Northern China operated on multiple plots totaling no more than 10mu (0.67 hectares), with an additional 10% operating on plots totaling no more than 30mu (2 hectares) (MARA 2022).

The production process of winter wheat by small farms in Northern China typically takes about 240 days and comprises five types of distinct yet sequential activities: ploughing, sowing, fertilizing and watering, weed and pest controls, and harvesting. These activities can be further grouped into three stages. In the first stage, which usually takes place in autumn (e.g., October), farmers plow the land and immediately sow the wheat seeds after harvesting the summer crops. The seeds remain underground throughout the entire winter season and sprout and tiller in the following spring, usually around March. During the second stage, which occurs between March and May, the wheat seedlings undergo rapid growth. Over this period of time, farmers engage in various activities to protect the plants, such as watering, fertilizing, and pest control measures. Towards the end of May or in the third stage, the mature wheat is harvested within a short time frame of less than 10 days, although the exact duration may vary across regions, before the rainy season begins. After harvesting, another rotating crop is planted. Throughout the entire growing season, each stage of wheat production involves distinct production methods or the utilization of varying combinations of labor and capital, as well as the output from the previous stage. The performance of each stage contributes proportionally to the final outcome, resulting in an entire production process for winter wheat in Northern China characterized by interdependence among stages.

Figure 1: Total wheat production and yield in Henan and Shandong and in China: 2010-2020



(a) total wheat production (Millon ton)



(b) wheat yield (ton/ha)

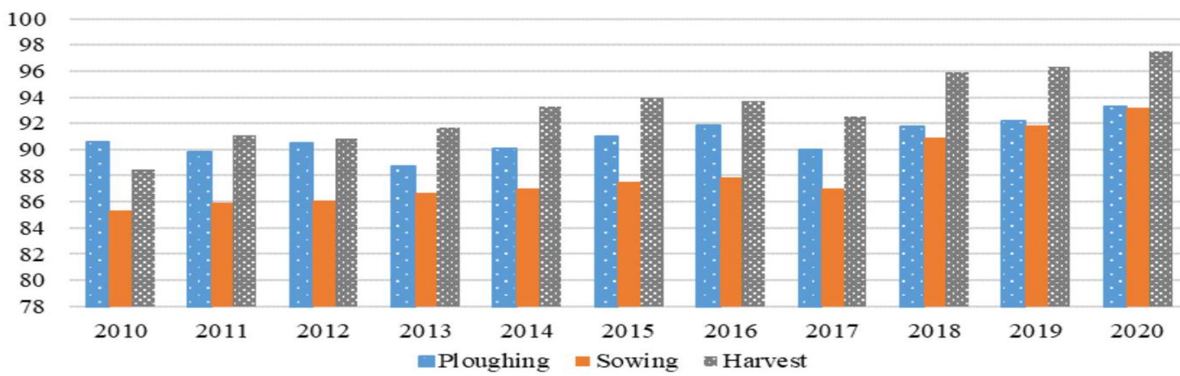
Source: China Rural Statistical Yearbook (2021)

Although operating on a small scale, wheat farms in Northern China have experienced significant growth in yield and productivity over the past two decades, primarily due to the increased mechanization. This rise in mechanization levels can be attributed, in part, to the widespread availability of agricultural mechanization services. Between 2000 and 2023, the overall level of agricultural mechanization in wheat production in Northern China has surged from approximately 35% to over 97%, with the total machinery power growing at an average annual rate of around 3%.

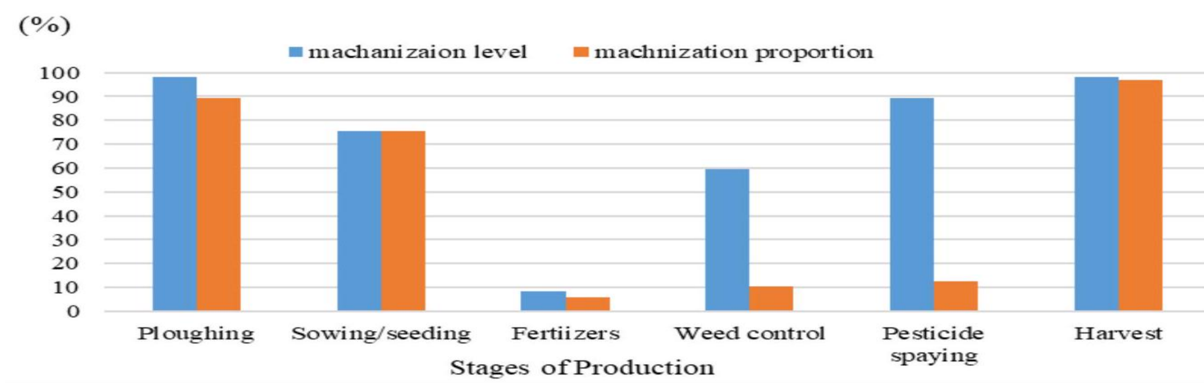
Alongside the gradual improvement in land consolidation and increased machinery purchase subsidies provided by the central and local government agencies, the rapid expansion of agricultural mechanization services provided by relatively larger farms and mechanization service organizations have played a crucial role in enhancing the level of mechanization in all stages of production for wheat farms in China, particularly for small-scale operations. In 2022, more than 4.2 million mechanization providers (accounting for around 10% of the total 39.95 million mechanization farms) and 194,845 mechanization service organizations enabled over 200 million farms to be equipped with better machinery throughout various stages of wheat production (MARA 2021). Driven by the improved level of mechanization in Northern China, among other amenable factors (e.g. use of new varieties and improved irrigation system), wheat farms have witnessed rapid growth in both yield and productivity. As is shown in Figure 1, the average wheat yield of these farms has increased by 1.3% per year over the past two decades.

Figure 2: Mechanization service in wheat production and its distribution by stage of production

(a) the number of service provides by types



(b) Mechanization level of wheat production (%)



(c) mechanization service in total capital input in 2021

Source: The CCAP farm survey data for 8 provinces in 2022.Chinese Agricultural Machinery Industry Yearbook (2021).

Numerous studies have analyzed the influence of agricultural mechanization services on farms' production performance both in China and other developing countries. On one hand, some studies have examined the influence of these services on production efficiency, off-farm employment, and social welfare of small farms. Overall, these studies have found that access to agricultural mechanization services allows small farms to save labor and enhance farm/agricultural productivity (Sheng et al., 2017). On the other hand, other studies have explored the factors that enable or hinder the development of agricultural mechanization services. These studies suggest that government subsidies for mechanisation service providers can have a positive impact on their utilization compared to self-owned machinery, thus contributing to improving agricultural productivity by increasing mechanization levels. Additionally, some studies also point out that the trading frictions between service providers and farm users, along with trading-related costs, can hinder the growth of agricultural mechanization services (Sheng et al., 2019; Daum et al., 2021; Caunedo and Kala, 2021). However, no consensus is reached regarding whether agricultural mechanization services can fully substitute self-owned machinery, or lead to complete mechanization in agricultural production in developing countries where small farms dominate.

Over the past two decades, China has emerged as a leader in promoting and adopting agricultural mechanization services. Initially, this trend was driven by the increasing private demand and supply due to a tightening labor shortage (Zhang et al., 2011). Subsequently, various government subsidies and support measures for agricultural machinery purchase and for mechanisation service providers further accelerate the uptake of these services (Bai, 2004; Zhang et al., 2017). However, in recent years, the expansion of agricultural mechanization services in China has encountered limitations (Figure 2). Take wheat production in Northern China as an example, where geographical characteristics such as land slope and small patches are unlikely to constrain mechanization applications. In the past, most mechanization services were provided by organized service providers who would travel across provinces (Yang et al., 2013). However, nowadays, the majority of these providers have been replaced by individual local farmers who own a tractor or a harvester and offer tailored services for specific stages of production (Sheng and Chancellor, 2019). Additionally, while the mechanization service levels for ploughing and harvesting have reached their peak, the overall quality of mechanization services remains relatively low and there is a significant disparity in the utilization of mechanisation services across different stages of wheat production, making it challenging to further improve farm productivity (Figure 2). Consequently, as farms increase their operational scale, there is a growing tendency for farmers to purchase their own machinery instead of relying on external service providers. The aforementioned phenomenon calls for a better explanation and warrants further research in this area.

3 Data Collection and Variables Definition

The data used in our study was obtained from a multi-period tracking farm survey conducted by the China Centre for Agricultural Policy (CCAP) in 2014, 2016, and 2021. The survey primarily focused on wheat-producing farms in two provinces, namely Shandong and Henan, located in

Northern China. The two provinces are well-known as major wheat production regions in China, which accounted for half of the country's wheat production. The survey was carried out immediately after the wheat harvest season, with the goal of collecting comprehensive information on inputs and outputs for wheat-producing farms. The collected data included land areas, yield, capital input, labor input, intermediate input, and mechanization services, at both the plot and farm levels. Particularly, the survey split the entire wheat production process of each wheat farm into three distinct production stages: the plowing/sowing stage, the plant protection stage, and the harvesting stage, which enable us to better understand the by-stage characteristics of wheat production. Consistent questionnaires were used throughout the three waves of surveys (i.e., 2014, 2016, and 2021), enabling the tracing of farms and the plots used for wheat production across the three survey rounds.

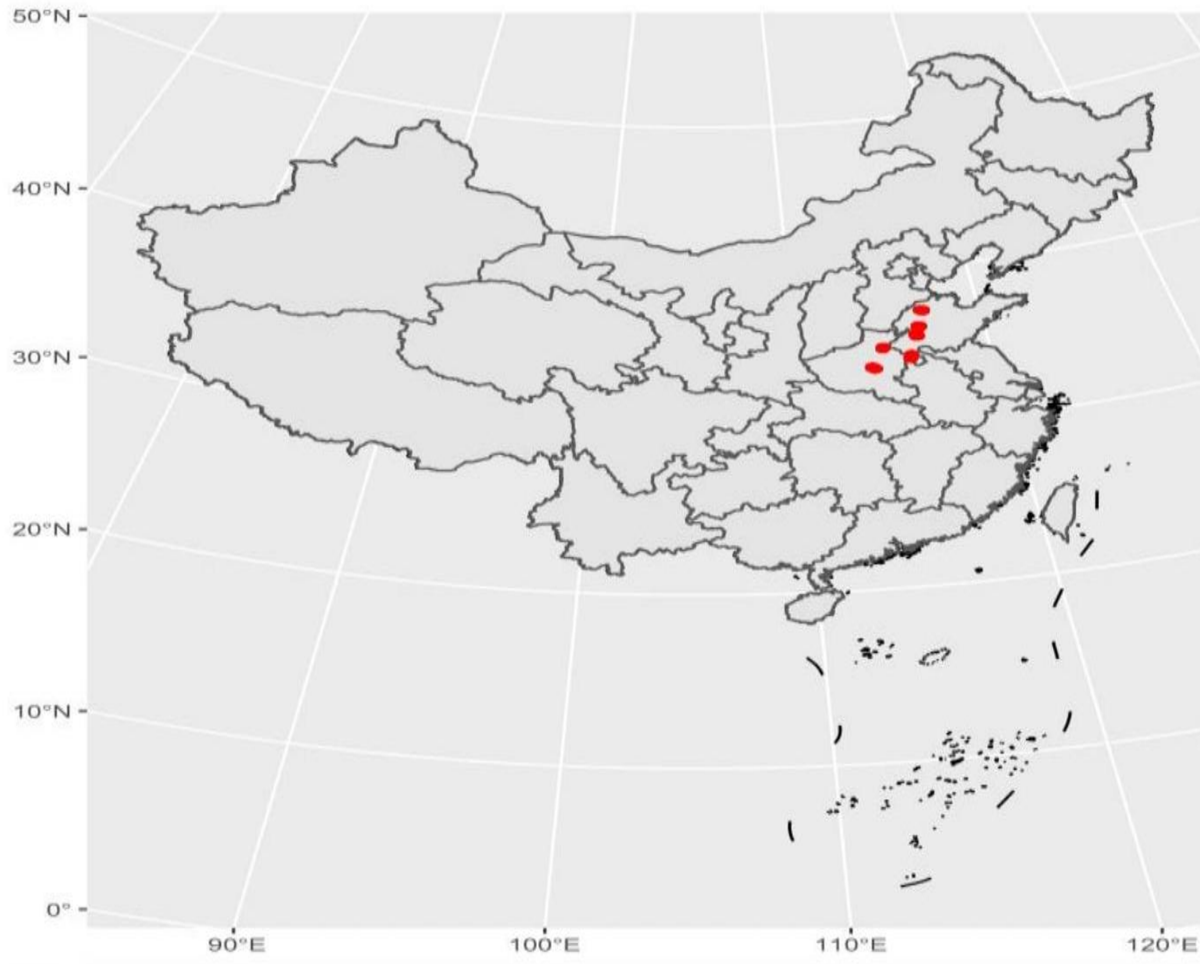
In the survey, we employed a stratified random sampling approach to select wheat-producing farms in the two wheat producing provinces, Henan and Shandong. Specifically, three wheat-dominant counties were randomly chosen from each province. In Shandong, the counties selected were Linyi, Wenshang, and Feicheng, while in Henan, the counties selected were Fengqiu, Yucheng, and Linying. Within each of the six counties, two townships were randomly designated, with each township representing either above-average or below-average levels of land consolidation. Two villages were then randomly selected from each township, resulting in a total of 12 townships and 24 villages. Finally, 10 households were selected from each village, and all households were categorized into two groups based on farm size (small and large farms). The cutoff point of 50mu (or 3.33ha) was used to differentiate between the two groups. From the small farm group, seven farms were randomly selected, while from the large farm group, three farms were chosen. If the total number of large farms was fewer than three, additional small farms were included to ensure a total of ten farms per village. In total, we conducted surveys on 240 wheat farms, out of which 95 farms were excluded due to incomplete data, outliers, and other statistical reasons. [3] The final sample used in our study consists of a balanced panel of 145 farms across the years 2013, 2015, and 2020.

Although our sample is limited to Henan and Shandong, we believe that it provides a good representation of wheat production in Northern China and the utilization of mechanization services in wheat farming, in particular for small farms. This is due to the fact that these two provinces host majority small wheat producers in China, accounting for 47% of the total wheat production in 2020 (NBSC 2021). Figure 3 displays the locations of the surveyed counties and their distribution within the wheat production belt of Northern China. Furthermore, a significant majority of wheat farms in Northern China allocated their entire land for wheat production during the winter-to-summer growing season. Our survey shows that 97.5% of wheat farms in the sampled villages cultivated only wheat in the winter season of 2013, 2015, and 2020. As a result, the input-output

[3] Please refer to Appendix B for more a detailed discussion on the data cleaning process in this study.

relationship at the farm level can accurately reflect the characteristics of wheat production in Northern China.

Figure 3: Geographical distribution of sample wheat production counties



Note: Each red dot in the map represents a county that we have surveyed in this study.

The key variables utilized in our study consist of inputs (such as land, capital, labor, and intermediate inputs) and outputs related to wheat production at the farm level, categorized into three distinct production stages. These stages consist of plowing/sowing, plant protection, and harvesting, effectively consolidating six types of sequential farming activities based on timing requirements and task similarities. The output for the harvesting stage, as well as for the entire wheat production process at the farm level, is proxized by using the wheat yield. It is measured as total wheat output dividing by the total wheat cropping area. Since the outputs for the plowing/sowing and plant protection stages cannot be directly observed, we proxized them by

[33] It's worth noting that winter wheat and summer maize are cultivated in rotation within the two provinces. Winter wheat is typically sown at the end of September, following the maize harvest, and harvested in June of the following year.

[4] Please refer to Appendix A for detailed discussion on data compilation.

using an estimated average crop growing index which is derived from the plot-level satellite remote-sensing image data collected for the corresponding production stage.

The detailed procedures for measuring the crop growing index for the plowing/sowing and harvesting stages are as follows. Firstly, during the survey, the farmers were asked to accompany the interviewer to visit all plots for wheat production. Using the GPS and electronic mapping tools, the interviewers marked and plotted the location and shape of each plot for wheat production on the map. Secondly, with the help of electronic maps indicating the locations and shapes of each wheat plot, we utilized Landsat Satellite Imagery (LSI) data captured in 2013, 2015, and 2020 respectively to calculate the average value of the Normalized Difference Vegetation Index (NDVI) for the plowing/sowing and crop protection stages in the sample year. For the plowing/sowing stage, the timeframe spanned from November 1st of the previous year to March 1st of the current year. Whereas, for the plant protection stage, the timeframe spanned from March 1st to June 15th. Once we obtained the NDVI for the two production stages, we weighted sum the estimated NDVI for all wheat plots to the farm level. To ensure comparability of the NDVI across the three stages, we also normalize the by-stage NDVI against the wheat yield by using a regression analysis. In general, a higher NDVI corresponds to a higher wheat yield while allowing for the by-stage production characteristics.

We have categorized inputs for wheat production into four categories: land input, capital input, labor input, and intermediate inputs, segregated by three different production stages. Land input is determined by calculating the overall value of land per household in real term.[4] This land value is assessed through a Hedonic function analysis of various factors, such as the total nitrogen content of the land, total organic carbon content of the land, land fragmentation, and the average distance from the farmer's home to the wheat plots. [5] Capital input for wheat production in different stages is measured by using the total value of capital services, adjusted for inflation and depreciation using the agricultural capital investment price index. It includes both capital input from self-owned machinery and mechanisation services. Labor input for each stage of wheat production is evaluated by tallying the total number of hours worked, including both hired and self-employed workers. Intermediate inputs are measured by aggregating the materials used for wheat production in each stage, including seeds, fertilizers, pesticides, irrigation/water, and mulching film etc. The quantity of these inputs is based on their corresponding values deflated by the corresponding price index, providing an approximation of their total quantity in use. Additionally, we have also distinguished between capital services from self-owned machinery and from mechanisation services for each stage of production.

[4] For further discussion on the estimation of inputs and outputs for wheat production by stages, please refer to Appendix B

[5] Please refer to Appendix C for a more detailed discussion on the method that we used to adjust land quality.

Table 1: Descriptive statistics on major variables of wheat farms in North China

	Average		2 0 1 3		2 0 1 5		2 0 2 0	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Wheat yield (kg/ha)	8865.9	23205.9	7823.7	15004.2	8332.7	22372.0	10441.4	29773.4
NDVI index at ploughing stage	6321.8	20172.1	3046.8	5958.2	9165.4	29936.1	6753.3	16442.9
NDVI index at plant protection stage	10142.5	28153.6	7057.8	14239.0	12279.3	35531.5	11090.3	29970.6
Capital input (yuan)	3103.5	9770.7	2705.1	5984.7	2808.1	7941.3	3797.4	13669.8
Ploughing/Sowing stage	1649.4	4758.8	1516.0	3167.4	1527.4	4119.0	1904.6	6392.1
Plant protection stage	394.3	2202.0	173.9	1069.1	260.5	1397.3	748.4	3356.0
Harvesting stage	1059.9	3228.5	1015.1	2302.9	1020.1	2828.2	1144.4	4238.3
Labor input (yuan)	142.4	460.8	147.7	283.1	136.7	596.2	142.9	448.7
Ploughing/Sowing stage	23.1	217.3	21.7	54.5	22.3	343.2	25.3	144.7
Plant protection stage	109.8	274.2	117.3	223.2	102.5	292.5	109.7	300.3
Harvesting stage	9.5	56.8	8.8	31.5	11.9	86.59	7.9	34.4
Land input (yuan)	8407.2	29054.5	11182.1	30768.4	4622.8	14197.3	9416.8	36902.6
Seed input (yuan)	1200.0	3885.6	974.7	2209.4	1116.7	3344.7	1508.6	5392.9
Intermediate input (yuan)	3955.6	11405.9	3317.6	7167.2	3989.6	12261.3	4559.4	13707.5

Note: All inputs are calculated at the 2013 constant price. The numbers in this table are arithmetic averages.

Table 1 provides the descriptive statistics of major input and output variables used in this paper. The wheat yield at the farm level has increased from 6.9 tonne per hectare to 8.0 tonne per hectare between 2013 and 2020, representing an annual growth rate of 2.1%. This growth in wheat yield is consistent with the national statistics reported by China National Bureau of Statistics (CNBS), which indicate that a 2.0% annual growth rate for wheat yield at the national level for the same period. These findings suggest that our sample provides a good representation for wheat production in China. In addition to the substantial increase in wheat yield, average farm size and the capital-labor ratio have also experienced significant increase. From 2013 to 2020, the farm-level capital-labor ratio (at the 2013 constant price) rose from RMB 22.8 yuan per working hour to RMB 28.4 yuan per working hour. This change can be attributed, in part, to the widespread availability of mechanization services, which have played a crucial role in enhancing both capital-labor ratio and wheat yield. During the 2013-2020 period, the proportion of wheat farms utilizing mechanization services increased from 65% to 96%.

However, when decomposing the farm-level wheat production into three different production stages, we show that different stages of wheat production have exhibited different characteristics in terms of the utilization of capital and labor over the sample period of 2013-2020. For instance, the plant protection stage stands out with a significantly lower capital-labor ratio compared to the plowing/sowing and harvesting stages, where mechanization services are widely used as a substitute for self-owned machinery. On average, the capital-labor ratio (at the 2013 constant price) for the plowing/sowing stage and harvesting stage is RMB 110 yuan per working hour and RMB 171 yuan per working hour, respectively, whereas it is only RMB 4.0 yuan per working hour in the plant protection stage. Additionally, the growth of mechanization services in both the plowing/sowing and harvesting stages surpasses that of self-owned capital, but this does not apply to the plant protection stage.

4 Model Specifications and Estimation Strategy

To investigate the impact of mechanization services on different stages of wheat production, we begin by breaking down the entire wheat production process into three interconnected stages: plowing/sowing, plant protection, and harvesting. Next, we employ a multiple-stage production function to assess the relationship between inputs and outputs for each stage of production and compute the stage-by-stage and the farm-level productivity of wheat farms. This section presents the empirical model specification and outlines the corresponding empirical strategy to be utilized.

4.1 The Multiple-stage Production Function: A Baseline Model for Wheat Farm Analysis

The multiple-stage production function is an empirical approach that was initially developed by Antle (1983), Antle et al. (1994), Behrman et al. (1997), and Ortiz-Bobea (2013) to analyze the input-output relationship of a production process with multiple production stages. The fundamental concept of this approach is to conceptualize the decision-making of a producer in a multiple-stage production process as a dynamic optimization problem, where input decisions are made sequentially for different stages of production. In earlier studies, this approach focused primarily on capturing the distinct marginal impacts of capital and labor in different stages of production, taking into consideration the inter-stage linkages within the production process. However, in a recent study, Brandt et al. (2022) expanded the approach to incorporate intermediate inputs (apart from the outputs from the previous production stage) in the estimation of the multiple-stage production function, as additional identification conditions. Furthermore, they also measured and compared the productivity across different stages of production based on the gross output model.

We adopt the framework introduced by Brandt et al. (2022) to analyze the entire wheat production process, which consists of three stages that are sequentially correlated. These stages include the plowing/sowing stage, the plant protection stage, and the harvesting stage. With the initial conditions defined by weather condition and output/input market prices, wheat farms aim to maximize their profits by determining the desired output and allocating it among the three series-correlated production stages. At each stage, farms seek to minimize their total costs. The utilization of primary inputs, such as capital and labor, will then be made separately based on an cost minimization process, with the output from the preceding stage being utilized as intermediate inputs. Following the observation of the total output, farms are able to assess their productivity, which is a random variable influenced jointly by the technology employed and the prevailing conditions.

To illustrate how the multiple-stage production function captures the wheat production process, we write the decision-making process of farmers involved in the three sequential production stages as follows:

$$\mathrm{Max}_{\{x_1,x_2,x_3\}}\, E[\pi \mid \Omega] = E\left[py_3 \mid \Omega\right] - \sum_{s=1}^{3} E\left[r_s x_s \mid \Omega\right] - qz \tag{1}$$

where π is the farm-level profit, p is the output market price, y_3 is the final output of the production process, r_s is the price vector for inputs x_s at production stage s, q is the price vectors of non-timed or fixed inputs z (i.e. land), and Ω represents the state upon which the input decision is based. The general technology used by wheat farms can thus be represented by the by-stage production functions:

$$y_1 = f_1\left(x_1, z, \varepsilon_1\right) \text{ and } y_s = f_t\left(x_t, y_{s-1}, \varepsilon_t\right), \text{ for } s = 2, 3 \tag{2}$$

where ε_s is a random component in wheat production used to capture external shocks such as changing weather conditions and disease shocks, etc., and y_{s-1} is the output from the immediate previous stage, which contains the effect of all inputs and random components in earlier production stages. It is to be noted that Equation (2) possess a recursive structure, and substituting y_1 and y_2 into y_3 will generates a composite production function:

$$y_3 = F\left(x_1, x_2, x_3, z, \varepsilon_1, \varepsilon_2, \varepsilon_3\right) \tag{3}$$

The sequence of input decision can thus been made as follows: In the first stage, wheat farms choose x_1 and z based on the initial state, future wheat output and decision rules for future optimal inputs x2$*$ and x3$*$, as given by

$$\begin{aligned} x_2^* &= x_2^*\left(r_2, y_1, \omega_2\right) \\ x_3^* &= x_3^*\left(r_3, y_2, \omega_3\right) \end{aligned} \tag{4}$$

where ω_s denotes the parameters of the subjective distributions of farms' decision at stage s given the future output and prices. Thus, wheat farms choose x_1 and z in the first stage by solving

$$\text{Max}_{x_1}\, E\left\{[py_3 - r_1x_1 - rz - -r_2x_2^* - r_3x_3^*] \mid \omega_1\right\} \tag{5}$$

subject to (2) and (3). After x_1 is chosen, production begins; the disturbance of the first stage production, ϵ_1, is realized; and the state variable, y_1, is realized as well. Also, x_2 will be used to solve:

$$\text{Max}_{x_2}\, E\left\{\left[py_3 - r_1\text{x}_1^0 - rz^o - r_2x_2 - r_3x_3^*\right] \mid \omega_2\right\} \tag{6}$$

subject to (2) and (3). After x_2 is chosen, the second stage of production begins, disturbance ϵ_2 is realized, and the state variable y_2 is realized.

Finally, at the beginning of the third stage production stage, the wheat farmer observes y_2 and chooses the inputs for this stage of production x_3 to solve

$$\text{Max}_{x_2}\, E\left\{\left[py_3 - r_1x_1^0 - rz^o - r_2x_2^o - r_3x_3\right] \mid \omega_3\right\} \tag{7}$$

subject to (2) and (3).

The above three-stage production function (defined by (5)-(7)) can be estimated, if the by-stage production technology is assumed to take a specific estimable function form. The seemingly unrelated regression (SUR) method could be employed to estimate the input-output relationship for each production stage, as long as the by-stage productivity can be properly identified.

4.2 Estimation of Multiple-stage Production Function and By-stage Productivity

To estimate the multiple-stage production function, we further assume that the production function of wheat farms in each stage takes the Cobb-Douglas form, and each stage of production has its own productivity level.[6] Moreover, since the wheat production involves a continuous plant growing process, outputs of the earlier stages (although not directly observed by wheat farms) will serve as intermediate inputs for the production of the later stages. Thus, the empirical specification of the multiple-stage production function for wheat farms can be written as:

$$\begin{aligned} Y_{i1t} &= e^{w_{1it}+\varepsilon_{i1t}} L_{i1t}^{\alpha_1} K_{i1t}^{\beta_1} N_{it}^{\tau_1} \\ Y_{i2t} &= e^{w_{2it}+\varepsilon_{2it}} L_{i2t}^{\alpha_2} K_{i2t}^{\beta_2} N_{it}^{\tau_2} R_{i2t}^{\tau_2} \\ Y_{i3t} &= e^{w_{3it}+\varepsilon_{3it}} L_{i3t}^{\alpha_3} K_{i3t}^{\beta_3} N_{it}^{\tau_3} R_{i3t}^{\tau_3} \end{aligned}$$

where $Y_{1it} = R_{2it}$ and $Y_{2it} = R_{3it}$ denote outputs of stage 1 and 2 that serve as intermediate inputs for stages 2 and 3, while Y_{3it} represents the final wheat output. K and L denote capital and labor inputs at each stage of production, and w_{it} denote the Hicks-neutral technology progress or

[6] This assumption is made only for simplifying the empirical estimation process, and the results can be applied to other more complex production function forms.

productivity measure. Although the multiple-stage production function allows different stage of production uses different production technology, $Y_{1it} = R_{2it}$ and $Y_{2it} = R_{3it}$ reflects the intrinsic linkage across three stages of wheat production.

Taking the logarithm on both sides of Equation (8) and applying the first-order condition for the three-stage production function, we can re-write the above functions into the log-linear system, such that:

$$
\begin{aligned}
y_{i1t} &= \alpha_1 l_{i1t} + \beta_1 k_{i1t} + \tau_1 n_{it} + w_{i1t} + \varepsilon_{i1t} \\
y_{i2t} &= \alpha_2 l_{i2t} + \beta_1 k_{i2t} + \gamma r_{i2t} + \tau_2 n_{it} + w_{i2t} + \varepsilon_{i2t} \\
y_{i2t} &= \alpha_3 l_{i3t} + \beta_1 k_{i3t} + \gamma r_{i3t} + \tau_3 n_{it} + w_{i3t} + \varepsilon_{i3t} \\
y_{i1t} &= r_{i2t}, y_{i2t} = r_{i3t}
\end{aligned} \tag{9}
$$

Equations (9) have an advantage that it allows us to separate by-stage production from the white noise and to aggregate by-stage productivity to the farm level with the use of the Domar (1961) share as weights. Using the dynamic recursive process, Equations (9) can be reformulated into

$$
\begin{aligned}
& y_{i1t} = \alpha_1\gamma_2\gamma_3 l_{i1t} + \alpha_1\gamma_2\gamma_3 k_{i1t} + \alpha_1\tau_2\tau_3 n_{i1t} + \alpha_2\gamma_3 l_{i1t} + \alpha_2\gamma_3 k_{i1t} + \alpha_2\tau_2 n_{i2t} + \alpha_3 l_{i1t} + \\
& \alpha_3 k_{i1t} + \varepsilon_{it}
\end{aligned} \tag{10}
$$

where $w_{it} = w_{i3t} + \gamma_3 w_{i2t} + \gamma_3\gamma_2 w_{i1t}$ and $\varepsilon_{it} = \varepsilon_{i3t} + \gamma_3\varepsilon_{i2t} + \gamma_3\gamma_2\varepsilon_{i1t}$ are aggregate productivity and aggregate white noise, respectively. Intuitively, the aggregate farm-level productivity $\mathrm{w_{it}}$ is the weighted sum of by-stage productivity measures according to its relative importance in the whole production process (measured by using the output elasticity of intermediate inputs from the previous stage).

To estimate Equations (10), we adopt the inverse control function approach following Brandt et al. (2022). Specifically, we assume that the choices of primary inputs such as land, labor and capital in one production stage are interdependent of other stages. Given the output of the earlier stage is used as input in the production of the later stage, the optimal intermediate input demand in each stage of production is retrieved, which depends not only on the use of land, labor and capital in the same stage, but also on the amount of production required in the subsequent stage of production. Thus, the demand functions for intermediate inputs of the three production stages $\phi_{st}(\cdot), s = 1, 2, 3$ are thus written as follows:

$$
\begin{aligned}
e_{i3t} &= \phi_{3t}\left(k_{i3t}, l_{i3t}, n_{it}, w_{i3t}\right) \\
e_{i2t} &= \phi_{2t}\left(k_{i2t}, l_{i2t}, w_{i2t}, k_{i3t}, l_{i3t}, w_{i3t}, n_{it}\right) \\
e_{i1t} &= \phi_{1t}\left(k_{i1t}, l_{i1t}, w_{i1t}, k_{i2t}, l_{2t}, w_{i2t}, k_{i3t}, l_{i3t}, w_{i2t}, n_{it}\right)
\end{aligned} \tag{11}
$$

where $k_{ist}, l_{ist}, w_{ist}$ are capital, labor and productivity of stage $\mathrm{s}, \mathrm{s} = 1, 2, 3$, and n_{jt} the total number of plot used (or average plot size) in production.

The estimation of Equations (11) involves using other intermediate inputs to identify unobserved productivity in the plowing/sowing stage (w_{i1t}), and in the plant protection stage (w_{i2t}). These other intermediate inputs include seeds (e_{1t}), fertilizers, pesticides and other crop chemicals (e_{i2t}), as well as missilery other than land, labor and capital inputs. We can identify the unobserved productivity by using these other intermediate inputs, because $\phi_{st}(\cdot)$ is assumed to be strictly monotone in w_{sjt} for each stage of production (Ackerberg et al., 2015), conditional on the use of land, labor and capital input (k_{i3t}, l_{ijt}, n_{it}) and on the demand of downstream production stages. In addition, the scalar observable condition also holds in our setting due to the cross-stage interdependent assumptions of farms' input choice.

Using the above assumptions, we can estimate Equations (11) in sequence. Specifically, we first invert the demand function of the harvesting stage (or stage 3), estimate the production function of this last stage, and calculate the by-stage productivity, say $\widehat{w}_{i3t}$. Thereafter, we substitute the estimated $\widehat{w}_{i3t}$ into the intermediate input demand function for the planting protection stage, in which the only remaining unobservable is the by-stage productivity $\widehat{w}_{i2t}$. Then, we invert the demand function for the plant protection stage (or stage 2) to obtain a control function for the by-stage productivity w_{2jt} before estimating the production function for this second stage. Finally, we substitute both the estimated productivity of the harvesting stage (w_{3t}) and of the plant protection stage ($\widehat{w}_{i2t}$) into the intermediate input demand function for the plowing/sowing stage (or stage 1), and estimate the production function for the first stage.

$$
\begin{aligned}
w_{i3t} &= \phi_{3t}^{-1}\left(k_{i3t}, l_{i3t}, n_{it}, e_{3jt}\right) \\
w_{i2t} &= \phi_{2t}^{-1}\left(k_{i2t}, l_{i2t}, e_{i2t}, k_{i3t}, l_{i3t}, n_{it}, \widehat{w}_{i2t}\right) \\
w_{i1t} &= \phi_{1t}^{-1}\left(k_{i1t}, l_{1jt}, e_{1jt}, k_{2jt}, l_{2jt}, \widehat{w}_{i2t}, k_{3jt}, l_{3jt}, \widehat{w}_{i2t}\right)
\end{aligned} \tag{12}
$$

where Equations (12) provide the control functions (or the inverted demand function) for the three production stages, namely the harvesting stage, the plant protection stage and the plowing/sowing stage. The estimation of Equations (11) and (12) can be made by using the general method of moments (GMM).

Using the above procedure to estimate the multiple-stage production function has at least four advantages. First, the multiple-stage production function can properly capture the characteristics of wheat production segregated by different stages of production in which different farming techniques (i.e. the choice of capital and labor inputs) are adopted. Second, using quantities of inputs and outputs to estimate the wheat production function helps eliminate the price bias problem, allowing us to recover true marginal returns to primary inputs such as land, labor and capital. Third, the GMM estimation procedure corrects for the potential endogeneity problem in different stages of production, caused by the unobserved productivity and the use of primary inputs. The identification process is made by using the positive correlation between other intermediate inputs and unobserved productivity in each stage of production.

4.3 The Empirical Estimation Strategy

Using the estimated parameters for the multiple-stage production function, we design a three-step procedure to examine the role of mechanization services in affecting wheat farms' productivity, both by production stages and at the farm level.

First, we retrieve the input-output relationship from the estimated multiple-stage production, and calculate the productivity for each stage of wheat production. We then estimate the farm-level productivity using the Domar weight to aggregate the by-stage productivity measures.

Second, we examine the impact of mechanization services on by-stage productivity in the plant protection stage compared to those in the plowing/sowing stage and the harvesting stage. With the control of by-stage capital-labor ratio (or capital intensity), we regress by-stage productivity on the utilization of mechanization services, which is defined as the proportion of mechanization services in total capital input, such that:

$$w_{its} = \beta_0 + \beta_1 C_{\text{ratio}} + \beta_2 \left(\frac{K}{L}\right) + \gamma Z + u_i + v_t + e_{it} \tag{13}$$

where w_{its} is the by-stage productivity estimates, $\frac{K}{L}$ refers to the capital-labor ratio in each production stage and CS_{ratio} refers to the proportion of mechanization services in total capital input. u_i and v_t denote the farm fixed effect and technology progress common to all wheat farms over time.

Equations (13) is estimated by using the OLS, FE and kernel density regression (a non-parametric analytical approach) techniques. The estimator (β_1) captures the marginal productivity impact of increasing 1% of mechanization service in total capital input, when total capital-labor ratio holds constant. By examining the relationship between mechanization services and by-stage productivity, we expect to distinguish the different roles that mechanization services may play in different stages of production. In addition, we also examine the relationship between the utilization of mechanization services and farm-level productivity estimates, with the control of capital intensity.

Third, we also conduct a number of sensitivity analyses to examine the robustness of the production function estimations. This includes but not restricted to using the alternative regression techniques, such as the OLS and FE models, to re-estimate the multiple-stage production functions, using the aggregation approach to estimate the farm-level production function and productivity, using different empirical model specifications to re-examine the relationship between the utilization of mechanization services and the by-stage/farm-level productivity and among others.

5 Assessing Impact of Mechanization Services on Wheat Farms' TFP

In this section, we start with presenting the estimated multiple-stage production function, which outlines the input-output relationship for the plowing/seedling, plant protection, and harvesting stages. Thereafter, we calculate the productivity and capital intensity of each production stage and aggregate them to the farm-level by utilizing Domar weights. Notably, a significant disparity in productivity and capital intensity across different stages of wheat production is observed. Finally, we also investigate the impact of employing mechanization services specifically in the plant protection stage, in comparison to the plowing/seedling and harvesting stages. The main results are summarized in Table 2-5 and Figures 4-7.

5.1 Estimating the Multiple-stage Production Function

Capital and labor are the most essential inputs that determine wheat production across various stages, namely the plowing/seedling, plant protection, and harvesting stages. Therefore, our initial objective is to investigate the role of capital and labor in these three stages of wheat production by examining the specific input-output relationships. To achieve this goal, we segregated the farm-level input and output data into the three production stages, spanning the period of 2013-2020, and use the NDVI index derived from satellite-image data to approximate the stage-specific output in the plowing/seedling stage and the plant protection stage. Two different sets of models, including OLS and GMM, are employed to address potential econometric issues that may arise.

Table 2 presents the estimated by-stage wheat production function, with Columns (1)-(3), (4)-(6) and (7)-(9) representing the plowing/seedling, plant protection, and harvesting stages respectively. The first two columns display the estimated elasticities of land, capital, labor, and intermediate inputs from the farm fixed effect models with and without the adjustment for weights (i.e. OLS and OLSW), while the third column displays the estimation results from the GMM model. Beginning with the OLS model, the estimated output elasticities of capital for the plowing/seedling stage and the harvesting stage are 0.609 and 0.458, respectively. These values are statistically significant at the 1% level. In contrast, the estimated output elasticity of capital for the plant protection stage is 0.012, and it is also precisely estimated at the 1% statistically significant level.

Table 2: Estimated by-stage production function for wheat

	Panel (A) Results for Plowing/Seedling		
	OLS	OLSW	GMM
K	0.609***	0.556***	0.514***
	(0.047)	(0.011)	(0.076)
L	0.034	0.019**	0.192***
	(0.034)	(0.008)	(0.017)
A	0.299***	0.309***	0.333***
	(0.038)	(0.009)	(0.088)
County-FE	Y	Y	Y
Year-FE	Y	Y	Y
Return to scale	0.90	0.88	1.03
Observations	435	435	435
R^2	0.897	0.806	-
	Panel B Results for Plant Protection		
	OLS	OLSW	GMM
K	0.012***	0.018***	0.090***
	(0.004)	(0.001)	(0.001)
L	0.185***	0.183***	0.133***
	(0.015)	(0.003)	(0.037)
M	0.654***	0.641***	0.741***
	(0.021)	(0.005)	(0.115)
A	0.144***	0.135***	0.038
	(0.019)	(0.004)	(0.039)
County-FE	Y	Y	Y
Year-FE	Y	Y	Y
Return to scale	1.00	0.98	1.00
Observations	435	435	435
R^2	0.974	0.952	-

Panel C Results for Plant Protection			
	OLS	OLSW	GMM
K	0.458***	0.485***	0.433***
	(0.026)	(0.006)	(0.031)
L	0.047***	0.061***	0.063***
	(0.015)	(0.004)	(0.000)
M	0.462***	0.431***	0.450***
	(0.031)	(0.007)	(0.000)
A	0.039**	0.045***	0.007
	(0.020)	(0.005)	(0.009)
County-FE	Y	Y	Y
Year-FE	Y	Y	Y
Return to scale	1.01	1.02	0.95
Observations	435	435	435
R^2	0.979	0.959	-

Note: In the first column, K, L, M and A represent capital, labor, intermediate input and land input used for wheat farm production in Northern China. OLS and OLSW refer to the farm fixed effect model with and without the adjustment for farm weights, and GMM refers to the GMM model. The numbers in parentheses below the estimated coefficients are standard errors. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels.

While all the by-stage estimators have been improved when we employ the weighted OLS and GMM models to address the potential endogeneity problem, there remains a significant discrepancy in the estimated elasticities of capital between the plant protection stage and the plowing/seedling and harvesting stages. Based on the estimated GMM model, the output elasticity of capital for the plant protection stage is estimated to be 0.090. This estimator is only approximately one-fifth of the estimate for the plowing/seedling stage (0.514) and one-fourth of the estimate for the harvesting stage (0.433). The results suggest that the returns to capital in the plant protection stage are considerably lower compared to the estimates for the plowing/seedling and harvesting stages.

Similarly, when comparing the estimated output elasticities of labor across the three production stages, significant variations in the estimators also become evident. Across all three regression models, the estimated output elasticity of labor for the plowing/seedling stage is positive but the OLS estimator is imprecisely estimated, indicating the return to labor in this stage is not stable. Conversely, the estimated output elasticities of labor for the plant protection stage and the harvesting stage are both positive and statistically significant at the 1% level. However, the estimator for the plant protection stage is notably larger than that for the harvesting stage.

According to the GMM model, the estimated output elasticity of labor for the plant protection stage is 0.133, which is twice larger than the estimate for the harvesting stage (0.063), and both estimators are statistically significant at the 1% level. These results suggest that the return to labor in the plant protection stage is substantially higher than those in the plowing/seedling stage and the harvesting stage.

Combining the estimated output elasticities of capital and labor across the three production stages allows us to gain insights into the specific characteristics of by-stage wheat production in Northern China regarding input utilization. Particularly, for the plowing/seedling stage, the improvement in output primarily relies on increasing capital input, given that the estimated marginal return to labor (or output elasticity of labor) is large but unstable. In contrast, both capital and labor exhibit positive and significant marginal returns in the plant protection and harvesting stages. However, the plant protection stage relies more heavily on labor as a substitute for capital, while the harvesting stage relies more heavily on capital as a substitute for labor. Based on the GMM estimates, the ratio of the estimated output elasticity of capital to labor in the plant protection stage is 0.677 (e.g., $0.677 = 0.090/0.133$), which is approximately 10% of that in the harvesting stage (e.g., $6.873 = 0.433/0.063$). These results suggest that increasing the relative supply of capital to labor is likely to enhance the output of the plowing/seedling and harvesting stages compared to the plant protection stage.

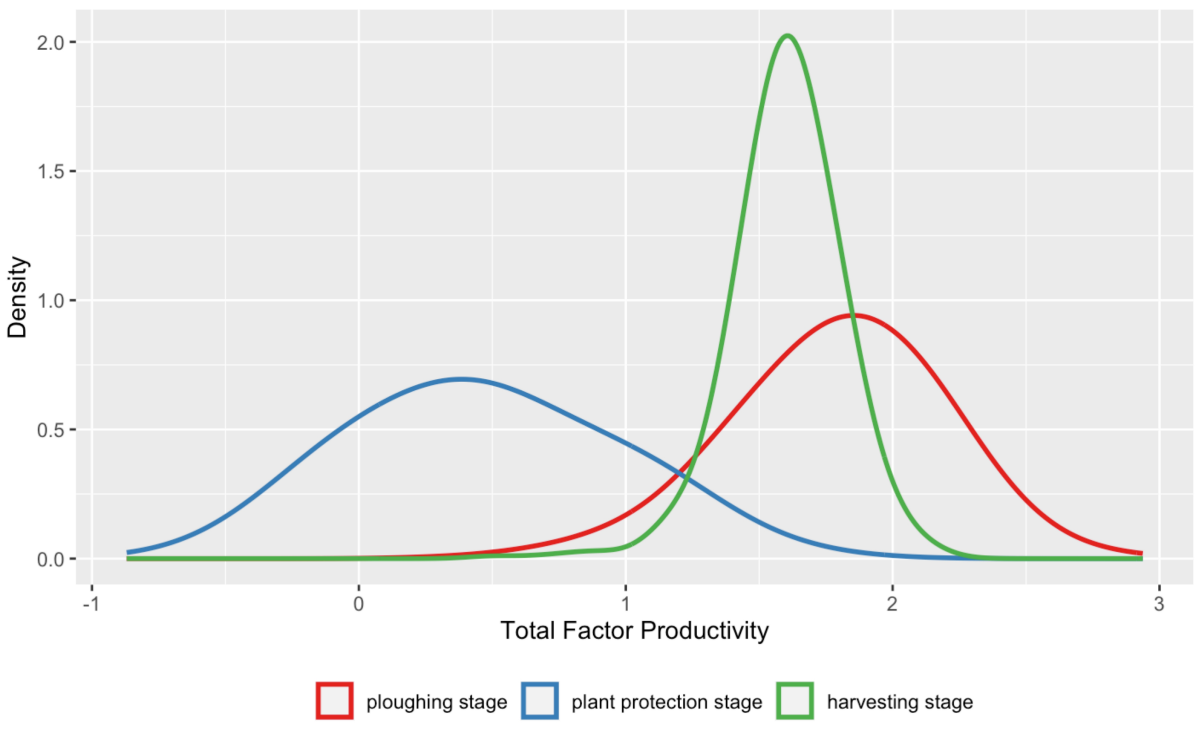
Our findings, based on the multiple-stage production estimates, have appropriately taken into account of the varying impact of land input (and the output of the previous stage or the immediate intermediate inputs) at different stages of wheat production across regions and over time. Across all model specifications, the estimated output elasticities of land (measured using the real land input with quality adjustment) in the three production stages are consistently positive and statistically significant at the 1% level in the plowing/seedling stage. Specifically, when using the GMM model, the estimated output elasticities of land for the plowing/seedling is 0.333 and statistically significant at the 1% level, while the estimators in the plant protection and harvesting stages are much smaller in magnitude, namely 0.038 and 0.007, respectively, and they are insignificant. This result suggests that land input plays an essential role affecting output of the plowing/seedling stage but not for the other two production stages.

Meanwhile, it is important to note that the output of the previous stage also serves as a significant input in subsequent production stages. Based on the GMM model, the estimated output elasticities of previous-stage output in the plant protection and harvesting stages are 0.741 and 0.450, respectively, both significant at the 1% level. This result implies that the three production stages are serially correlated. In other words, each stage of production influences the downstream (or upstream) stage through the supply (or demand) of unobserved outputs, thus generating spillover effects on aggregate productivity at the farm level. Additionally, each of the three stages of production exhibits a constant return to scale, with the sum of the input elasticities being close to one.

5.2 By-stage TFP Differences and Capital Deepening

Utilizing the estimators obtained from the multiple-stage production function, we further calculate the productivity for each stage of wheat production and aggregate them to the farm-level level. Figure 4 illustrates the kernel density distribution of the productivity estimates at each stage. The purple curve represents the productivity distribution of the plowing/seedling stage, the green curve represents the plant protection stage, and the blue curve represents the harvesting stage.

Figure 4: Comparing the kennel density distribution of by-stage TFP estimates (log)



Source:Authors estimates by using the by-stage production function.

Upon comparing the distributions of the by-stage productivity estimates, we observe that the average productivity estimate (in logarithm) for the plowing/seedling stage remains around 1.94, while that for the harvesting stage closely aligns at 1.60 . The distributions of the by-stage productivity estimates for both stages are centered on their respective means, and there is significant overlap between the two distributions. This result indicates that the productivity levels of the average plowing/seedling and harvesting stages are similar. Furthermore, there is no substantial difference in the average by-stage productivity estimates across farms for both the plowing/seedling and harvesting stages, the productivity distribution of the plowing/seedling stage is more flatten.

However, when considering the plant protection stage, the average by-stage productivity estimate decreases noticeably and becomes more diverse in distribution. As shown in Figure 4, the average by-stage productivity estimate (in logarithm) for the plant protection stage hovers around 0.51, accounting for only about 30% of the plowing/seedling stage and 25% of the harvesting stage. This result suggests that the average productivity estimate for the plant protection stage is significantly lower than those for the plowing/seedling and harvesting stages. Additionally, the distribution of the by-stage productivity estimates (in logarithm) for the plant protection stage exhibits a more flattening pattern, ranging from -1 to 3, with a wide and flat tail on the left-hand side. This result indicates that there are more substantial differences in the average by-stage productivity estimates across farms for the plant protection stage compared to the plowing/seedling and harvesting stages.

Why is the average productivity estimates for the plant protection stage lower compared to the other two production stages? To answer this question, we delve deeper into the relationship between productivity estimates and capital intensity, measured through the capital-labor ratio, for each of the three production stages. Figure 5, specifically Panels (a), (c), and (d), demonstrates a strong positive correlation between the by-stage productivity estimates and capital intensity, both for the plowing/seedling stage, harvesting stage, and at the aggregate farm level. This finding is further supported by our estimations of the by-stage production functions, as depicted in Table 2. The relatively higher estimate of output elasticity for capital to labor suggests that enhancing capital intensity, while holding other inputs constant, will lead to improved output in the plowing/seedling stage and harvesting stage. This result aligns with our expectations, as employing more machinery to substitute labor in these stages, particularly in activities such as plowing, seedling, and harvesting, can significantly enhance the productivity of wheat farms (Foster and Rosenzweig, 2022).

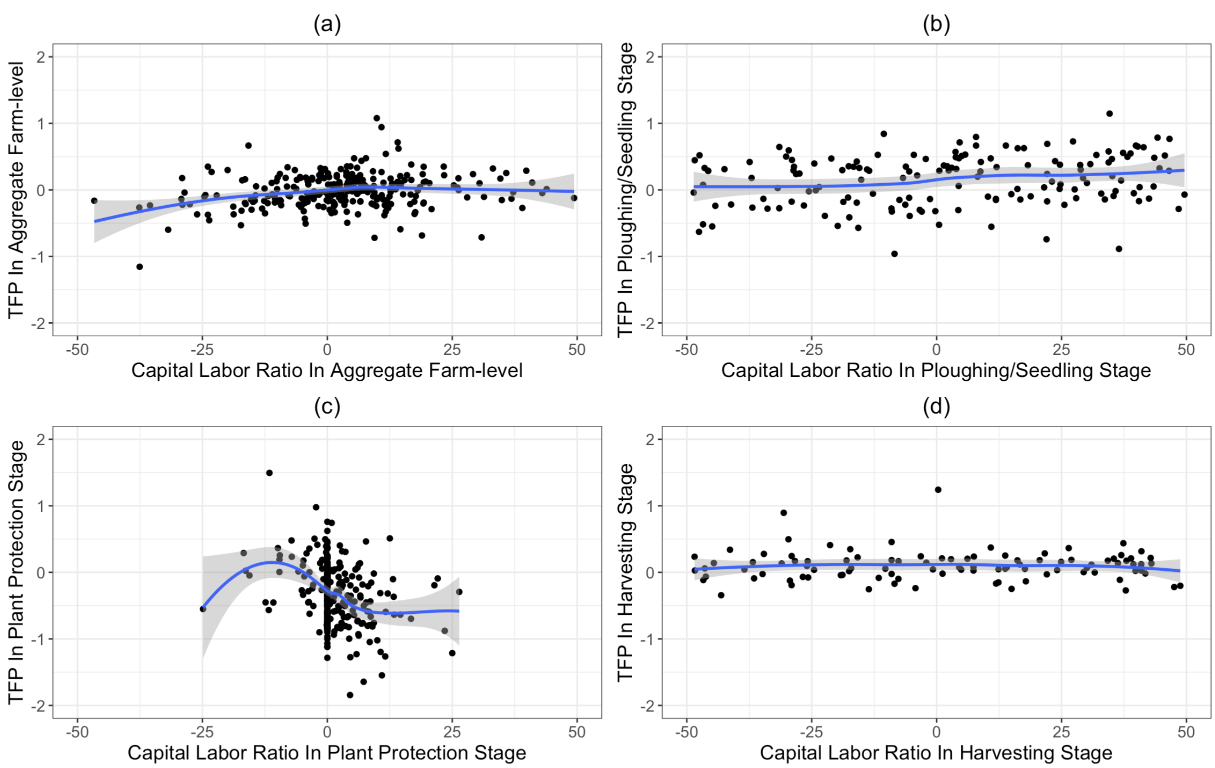
However, the positive correlation between the by-stage productivity estimates and capital intensity is not observed in the plant protection stage. Panel (c) of Figure 5 displays an evident non-linear trend, depicted by the LOWESS regression, which resembles an "S-shaped" relationship. Specifically, the by-stage productivity estimates for the plant protection stage initially increase with capital intensity when capital intensity stays at a relatively lower level, then start to decline as capital intensity rises. Yet, once capital intensity reaches a certain threshold, the by-stage productivity estimates begin to increase again. This finding implies that increasing capital intensity does not consistently contribute to productivity growth in the plant protection stage, unlike the other two stages. A possible explanation for this phenomenon is that most plant-protection activities are typically not time-sensitive or adaptable in their application. Therefore, wheat farmers may opt to substitute labor for capital in their farming practices if using capital does not result in cost savings. Yet, a comparison of relative labor wages is made across the three stages, we show that the labor cost in the plant-protection stage is similar as that in the other two stages, in particular when a proper quality adjustment is made for labor input. As is shown in Table 3, the average wage for labor the plant protection stage is around RMB 15 yuan per working hour (at the 2013 constant price) the wage gap across the three production stages is not large.

Table 3: Median Wages for Various Agricultural Production Stages (2013-2020)

Activity	Average (yuan/hour)	2013 (yuan/hour)	2015 (yuan/hour)	2020 (yuan/hour)
Plowing	15.39	13.85	15.39	28.13
Sowing	16.14	18.64	11.50	12.98
Fertilizing	13.49	10.00	14.78	20.92
Weeding	12.48	10.07	19.76	12.48
Pesticide Application	13.83	10.00	26.67	19.90
Harvesting	12.12	10.84	8.83	48.83

Note All wages are calculated at the 2013 constant price. The percentage of households having employment labor in plowing, sowing, fertilizing, weeding, pesticide application, and harvesting was 5.8%, 6.6%, 9.9%, 11.61%, 12.2%, and 6.5% respectively.

Figure 5: The relationship between capital intensity and farm TFP by production stages and at the aggregate farm level

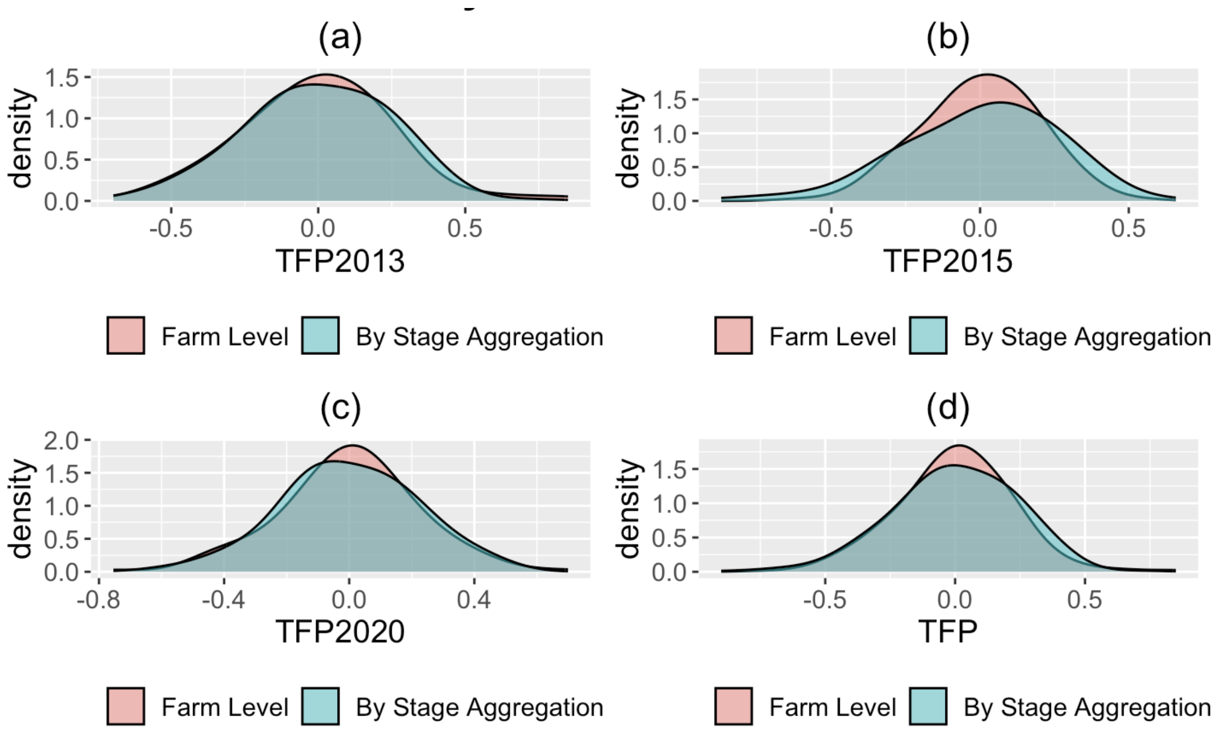


Note: x(capital labor ratio) and y(TFP) are both subtracted the values from period t-1 at the household level. Panel (a)-(c) represent the ploughing/seedling stage, the plant protection stage, and the harvesting stage respectively. Panel (d) represents the farm-level TFP against the capital-labor ratio. The fitting line is created using a LOESS (Locally Estimated Scatterplot Smoothing) method in R package ggplot2.

Next, we also aggregate the by-stage productivity to obtain the farm-level estimate by employing the Domar weights for each production stage. We then compare the distribution of the aggregate productivity estimates with that derived from the estimated farm-level production function. Figure 6 illustrates the distribution of the aggregate by-stage productivity estimates and the farm-level productivity estimates for three specific time periods (2013, 2015, and 2020), as well as for all sample years combined, when they are demeaned. The average productivity estimates obtained through the by-stage aggregation (in the demeaned form) closely align with those of the farm-level estimates, indicating that the productivity estimates at the farm level can be effectively decomposed and explained by the productivity estimates of the three production stages. However, the distribution of the aggregated by-stage productivity estimates appears to be flatter than that of the farm-level estimates. This result suggests that the productivity estimates derived from the farm-level production function tend to underestimate the variations in productivity across farms caused by the aggregation process.[7] Additionally, the plant protection stage is chain-linked with other stages of production, the lagged productivity in the plant protection stage may impede the enhancement of productivity at the farm level.

[7]In our specific case, the plant protection stage exhibits relatively lower productivity compared to the plowing/seedling stage and the harvesting stage (as shown in Figure 6). This disparity may depress the farm-level aggregate productivity during the aggregation process and consequently contribute to the amplification of productivity differences at the farm level.

Figure 6: Comparing the distribution of aggregated by-stage TFP estimates with that of the farm-level TFP estimates: all sample vs. by time period



Note:the data are obtained from using both the by-stage and the farm-level production functions.

5.3 Impact of Mechanization Services on Farm TFP

It is widely recognized that the rapid expansion of mechanization services has substantially contributed to improve mechanisation levels across all stages of wheat production in Northern China. Between 2013 and 2020, agricultural mechanization services have experienced double-digit growth rates and, on average, have contributed to over 80% of the capital input at the farm level for wheat production, served as a substitute for self-employed capital. Based on our sample, increased use of mechanization services has also played an important role in promoting the farm-level productivity growth for the 2013-2020 period.[8] However, it remains uncertain how the utilization of mechanization services has affected the by-stage and aggregate farm-level productivity of wheat production.

To investigate the impact of mechanization services on by-stage productivity, we calculate the proportion of mechanization services in capital input for each stage of wheat production and analyze the influence of mechanization services on by-stage productivity estimates through regression

[8]In our specific case, the plant protection stage exhibits relatively lower productivity compared to the plowing/seedling stage and the harvesting stage (as shown in Figure 4). This disparity may depress the farm-level aggregate productivity during the aggregation process and consequently contribute to the amplification of productivity differences at the farm level.

analysis. Table 4 provides the descriptive statistics on farms' mechanization level and the proportion of farms using mechanization services by five types of production activities throughout the wheat production process in Northern China. The five production activities include ploughing, sowing/seedling, fertilizing, weed/pest control, and harvesting, which could be re-grouped into the three stages of production, such as the plowing/seedling stage, the plant protection stage and the harvesting stage.

On average, the mechanization level of the ploughing/seedling stage and harvesting stage in wheat production in Northern China exceeds 99%, which is significantly higher than the level observed in the plant protecting stage encompassing activities such as fertilizing, weed and pest control (ranging from 9% to 32%). This indicates that wheat farms rely less on capital to replace labor in the plant protecting stage. Furthermore, when comparing the proportion of farms utilizing mechanization services across different production activities, we find that the percentage of farms using mechanization services (2-7%) is even lower for the plant protecting stage compared to the ploughing/seedling stage (76-79%) and the harvesting stage (89%). This result suggests that the introduction of mechanization services has had limited impact on improving the mechanization level in the plant protecting stage compared to its effect on the ploughing/seedling and harvesting stages.

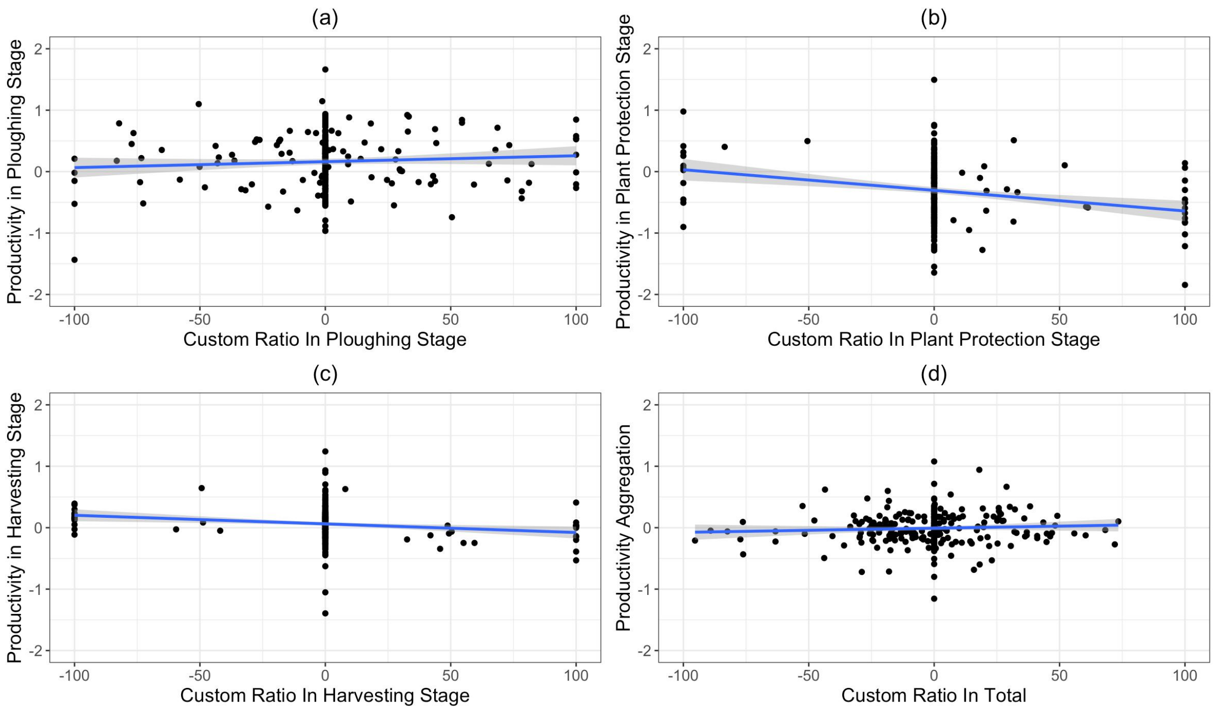
Table 4: Average mechanization level and proportion of mechanization service in wheat production 2013-2020: By production stage

	Average		Shandong		Henan	
	Mech. level (%)	Mech. service share (%)	Mech. level (%)[a]	Mech. service share (%)	Mech. level (%)[a]	Mech. service share (%) [b]
Plough	99.8	79.5	100	78.8	99.6	80.1
Sow	98.9	76.3	98.9	79.4	98.8	74.0
Fertilize	9.2	2.5	7.9	1.6	10.2	3.3
Weed control	25.7	3.2	25.4	4.8	26.0	2.0
Pest control	31.7	7.1	34.9	13.2	29.3	2.4
Harvest	99.8	89.0	99.5	80.4	100	95.5

Note:[a] represents the percentage of wheat farms using machinery in the five production stages; [b] represents the proportion of wheat farms using mechanization services in the five production stages.

Next, we also investigate the correlation between by-stage productivity and the proportion of mechanization services through regression analyses. Figure 5 displays the nonlinear relationship between by-stage productivity and the proportion of mechanization services for the three production stages and at the aggregate farm level, utilizing the LOWESS regressions. Generally, the estimates of by-stage productivity show an upward trend as the proportion of mechanization services increases in the ploughing/seedling stage and harvesting stage. However, in the plant protection stage, the by-stage productivity estimates tend to decrease, especially when the proportion of mechanization services reaches a certain threshold.

Figure 7: The Relationship Between TFP And Custum Ratio Accross Different Stages



Note: x(custom service ratio) and y(TFP) are both subtracted the values from period t-1 at the household level. Panel (a)-(c) represent the ploughing/seedling stage, the plant protection stage, and the harvesting stage respectively. Panel (d) represents the farm-level TFP against the capital-labor ratio.

The relationship between by-stage productivity and the proportion of mechanization services for the three production stages is also confirmed through kernel density regressions. Table 5 presents the estimated impact of the proportion of mechanization services on by-stage productivity estimates, while controlling for capital intensity in each production stage. As depicted in Column (3), the estimated impact of mechanization proportion on by-stage productivity in the plant protection stage is negative and statistically significant at the 5% level. This is in contrast to the impacts observed in the ploughing/seedling stage and the harvesting stage (Columns (2) and (4)), where the estimated productivity impact is either positive or insignificant. It suggests that increasing use of mechanization services may have a negative effect on by-stage productivity in the plant protection stage. One possible explanation for this phenomenon is: since wheat farmers could not observe the performance in the plant protection stage, they will choose to minimize the costs by choosing the service providers with low relatively quality. Consequently, the presence of potential adverse selection by wheat farmers for mechanization services in the plant protection stage weakens its effectiveness as a substitute for self-owned machinery as well as for labor. As the farm-level productivity is the weighted sum of by-stage productivities, the relatively lower productivity caused by using mechanization services in the plant protection stage may impede the overall farm-level productivity.

Table 5: Adjusted Estimated Impact of Mechanization Service on by-Stage TFP

	(1) Ploughing/Seedling	(2) Plant Protection	(3) Harvesting	(4) Overall
K-L ratio	0.001**	-0.009***	0.000	-0.001
	(0.001)	(0.003)	(0.000)	(0.001)
Mechanization proportion	0.004**	-0.002**	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Farm-level fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Number of Observations	435	435	435	435
R-squared	0.744	0.708	0.452	0.545

Note: The dependent and independent variables in Column (4) are computed at the aggregate level, while in Columns (1)-(3), are computed with respect to the ploughing/seedling stage, the plant protection stage, and the harvesting stage, respectively. All model specifications have included the farm-level fixed effects and the year fixed effects to control for unobserved time-invariant farm-specific characteristics and common temporal shocks, respectively. The numbers in the parentheses following the regression coefficients are standard errors. Standard errors are clustered at the village level in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

6. Robustness Checks

While the above analyses have provided some useful insights, there remain some concerns of potential measurement errors that could contaminate our estimation results. In this section, we carry out a set of robustness checks to examine the sensitivity of our findings.

First, it is believed that wheat production in different stages may face different labor wages. For example, the labor wage is usually higher in the plowing/seedling stage and the harvesting stage, while lower in the plant protection stage. Since farmers are likely to use the relatively cheaper labor to replace capital in the plant protection stage, the relative lower labor wage in the plant protection stage could bias our estimation. To deal with this problem, we re-estimate the difference in labor wage by using the farm survey data for different stages and use them to adjust the labor use in different stage of production. The estimation of the by-stage production function and productivity are generally consistent with the results from the main context.

Second, there are concerns that the satellite-based and remote-sensor based measure of by-stage wheat output may not be linearly correlated with the final farm output (e.g. wheat yield), which may affect the reliability of our estimation. For example, a higher NDVI index on the plot does not necessarily mean that the farm will have a good yield from a biological perspective. In practice, there are many unobserved factors, such as weather condition, particular time for data collection and so on, that could affect the measured NDVI index and its quality of the NDVI index to approximate the by-stage output. To address this potential measurement error, we take a weighted average of the NDVI indexes observed by different time periods for the particular production stages and on different plots owned by farm. The weights are determined using a linear regression approach. The estimation results are consistent with the results from the main context. Overall, the impact of mechanization services on the by-stage productivity is negative in the plant protection stage, but positive in the seedling stage.

Third, it is argued that the choice of different initial value for the parameters (i.e. the elasticities of capital and labor) may affect the final estimation results. To examine the sensitivity of our estimation to the choices of initial values, we re-do the estimation of the multiple-stage production function, re-calculate the by-stage productivity and examine the relationship between mechanization service in use and the by-stage productivity. Generally, the estimation results by using various initial values on the elasticities of capital and labor are generally consistent with the results that we have obtained from the main context.

Overall, these robustness checks demonstrate that the main findings are not sensitive to different wage assumptions or potential measurement errors in the NDVI data, strengthening the credibility of the conclusions drawn from the primary regression analysis.

Table 6: Robustness Checks for Different Methods

	RC1			RC2			RC3		
	S1	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
K	0.454***	0.102***	0.395***	0.531***	0.094***	0.403***	0.524***	0.155***	0.323**
	(0.022)	(0.009)	(0.023)	(0.030)	(0.004)	(0.040)	(0.148)	(0.059)	(0.144)
L	0.262***	0.117***	0.105***	0.255***	0.169***	0.085***	0.210***	0.229*	0.110
	(0.012)	(0.014)	(0.000)	(0.008)	(0.032)	(0.000)	(0.030)	(0.134)	(0.098)
M	-	0.690***	0.450***	-	0.683***	0.450***	-	0.526**	0.471***
	-	(0.055)	(0.000)	-	(0.069)	(0.000)	-	(0.201)	(0.098)
A	0.318***	0.102*	0.000	0.245***	0.083**	0.012	0.251	0.116	0.058
	(0.022)	(0.055)	(0.000)	(0.021)	(0.034)	(0.011)	(0.158)	(0.165)	(0.163)
County-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Return to scale	1.03	1.03	0.95	1.03	1.01	0.95	0.98	1.02	0.96
Observations	435	435	435	435	435	435	435	435	435

Note: RC1 re-do the estimation by adjusting for the difference in labor wages by production stages, 30 yuan for Plowing/Seedling, 19 yuan for Plant Protection, 22.5 yuan for Harvesting. RC2 re-estimate the by-stage NDVI by using the quadratic function form. RC3 allow the sum of initial value of input to range from [**0.95,1.05**].

7. Conclusions

The rapid expansion of mechanization services has played a pivotal role in increasing capital-labor ratio and productivity of wheat production in Northern China where small farms are predominant. However, little is known about how mechanization services affect the productivity of small farms operating across multiple production stages. This paper investigates the adoption of mechanization services by small wheat farms in a multiple-stage production process, and evaluate their productivity effects, both at each stage and overall. We empirically estimate a multiple-stage production function by using a unique panel data of 145 wheat farms in Northern China for the period of 2013-2020, which consists of detailed by-stage input and output information.

We show that, when controlling for by-stage characteristics, mechanization services are likely to have a negative effect on the productivity of the plant protection stage, which in turn hampers the further increase of capital intensity and productivity at the farm level. We then developed a simple model to explain the phenomenon. Since the performance of service providers are not directly observable in the plant protection stage, farmers opt to adverse select less use of mechanisation services for self-owned machinery, which not only negatively affect the capital intensity and by-stage productivity but also decrease the farm-level productivity by generating the adverse spill-over effects to the downstream stage of production. These findings provide valuable insights into whether selecting service providers and service packages based on the stage of production, while satisfying the cost-minimization condition for each stage, would be an optimal choice for small-farm users of mechanization services seeking to enhance productivity.

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Appendix A. A Theoretical Model on Mechanization Service

To illustrate the mechanism behind our empirical model, we develop a simple theoretical model in this appendix to describe the potential impact of mechanization services on capital deepening at different production stages of wheat farms in Northern China. To the farmer, a "season" is a distinct period of the year during which a stage of agriculture (such as planting and harvesting) is optimally undertaken. For example, for spring wheat grown on the northern Great Plains, the month long planting season usually begins in April, and the harvest season is primarily restricted to August. This broad definition of a season, however, hides some important features of nature that directly influence the incentives inherent in agricultural production. We first model seasonality as parameter: S, the number of stages in the process;

Consider a representative wheat-specialized farm who uses a multi-stage production technique to grow wheat. Since farm production is cumulative, our model uses a stage production function that depends on natural parameters and specialization. Let Q be the final consumer product (such as bacon or bread) derived from a cumulative production process with S discrete stages of production. The output in each stage is an input into the next stage's production function. In each production stage, the farm will use capital (K_s) and labor (L_s) (where $\mathrm{s} = 1, 2$ and 3), depends on the output of the previous stage, as inputs. $\bar{K}$ is capital input and $\bar{L}$ is labor input. So we have:$Q = q_s = F\left(K_s, L_s; q_{S-1}\left(q_{S-2}(\ldots)\right)\right) = F\left(K_s, L_s; q_{-1}\right)$. At each stage the output depends on farmer effort (L_s), capital input (K_s). Hence, the farmer in our model takes the output from a previous stage as an input into the next stage and makes an optimal effort choice that depends.

Combing all the three stages, the farm will maximize total profits by choosing capital and labor for each stages, given the predetermined output of the previous stage, such that:

$$\begin{gathered} \max \pi = pQ - \sum_{s=1}^{N} rK_s - \sum_{s=1}^{N} wL_s \\ \text{s.t. } \sum_{s=1}^{N} K_s \leq \bar{K}, \sum_{s=1}^{N} L_s \leq \bar{L} \end{gathered} \tag{A1}$$

We then assume that there is perfectly competitive labor and capital market, such that r is interest rate (or the market price of capital input) and w is wage for labor (or the market price of labor). The $\boldsymbol{r}$ and $\boldsymbol{w}$ is the same across different stages. We can make the assumption because all wheat farmers in Northern China are small-scale farms and each farm's behavior will not affect the market price. An equilibrium is thus determined by a set of decisions and factor prices (w, r), such that the choice of capital and labor (K, L) solves the representative farm's profit maximization process.

We assume that F is concave in (K, L) and take the first order condition of (1). It is straightforward to see that equilibrium factor prices equal to the marginal products of inputs.

$$\begin{cases} w = \frac{\partial F\left(K_s^i, L_s^i, q_{-1}\right)}{\partial L_s^i} \\ r = \frac{\partial F\left(K_s^i, L_s^i q_{-1}\right)}{\partial K_s^i} \end{cases} \quad \forall i \in \{1, 2, \ldots, N\}, \forall s \in \{1, 2, \ldots, S\} \tag{A2}$$

To simplify the analysis, we further assume that in each stage of production $s \in \{1, 2, 3\}$, the farm will use the same amount of labor such that $L_1^i = L_2^i = L_3^i = \overline{L^i}$ (or labor is fixed in each stage). Based on this assumption, we can thus normalized capital intensity (or capital-labor ratio) for each production

stage as $k_s^i = \frac{K_s^i}{L_s^i} = \frac{K_s^i}{\overline{L^i}}$. Thus, the by-stage production function can be simplified as: $F\left(K_s, L_s; q_{-1}\right) = A_s h\left(k_s^i; q_{-1}\right), \quad A_s$ is an efficiency parameter.

A.1: Agricultural Production Characteristics and the By-stage Choice of Capital and Labor Input

To incorporate the characteristics of different stages of wheat production into our analysis, we define two parameters that could distinguish between different production stages. One is the degree of capital specialization (α_s), or how easy the tasks in the particular stage of production could be will be implemented by capital equipment. Since new technologies are likely to be embodied in the capital equipment and it will not need to be monitored, we have that increasing capital investment will help to improve production efficiency. The other is the number of tasks (T_s), Typically, when number of tasks increases, the length of time increases. T_s captures the potential moral hazard, the complexity of the tasks and the time pressure for the work.

Because there are many tasks within a given stage, we define t_{st} as the effort in the s^{th} stage, on the t^{th} task, performed by a worker. Tasks are indexed by $t = 1, \ldots, T$; stages are indexed by $s = 1, \ldots, S$; Let T be the number of tasks for a given stage and assume that T is exogenous, determined by nature and technology. Tasks are well-defined jobs that take place during a stage, such as operating a combine or a grain truck during wheat harvest. To simplify, we assume that $t_{s1} = t_{s2} = \cdots = t_{sT}$.

The parameter α_s indicates the degree to which capital specialization can potentially increase output. For some tasks (such as shoveling grain) there may be little to be gained from specialization ($\alpha_s \approx 0$), while for others these gains may be great ($\alpha_s \approx 1$). When task number is large, it is hard for a machine to finish all the tasks, the α_s will decrease, so we can define the efficient technology for a single task as $a_{ts} = \left(\frac{1}{T_s}\right)^{\alpha_s} t_{s1}$, where a_{ts} is decreasing with T_s and increasing with α_s. And the gains brought by the specialization in mechanical engineering will decrease as T_s increases $\frac{\partial^2 \alpha_{ts}}{\partial \alpha \partial T_s} < \mathbf{0}$.

Under these assumptions, the full stage production function becomes:

$$q_s = A\left(\left(\frac{1}{T_s}\right)^{a_s} t_{s1}; \ldots, \left(\frac{1}{T_s}\right)^{a_s} t_{sT}\right) h\left(k_s; q_{-1}\right) = A\left(\alpha_s, T_s\right) h\left(k_s; q_{-1}\right), s = 1, \ldots, S \qquad \text{(A3)}$$

In (A4) k_s is a stage-specific (physical) capital input, h_s is the stage s production function, A($\cdot$) is the aggregate function for $\boldsymbol{a}_{ts}$

By incorporating the two parameters into the by-stage production function, we have

$$q_s = A_s(T, \alpha) h\left(k_s^i; q_{-1}\right) \text{ where } \quad h'(.) > 0 \text{ and } h''(.) < 0 \qquad \text{(A4)}$$

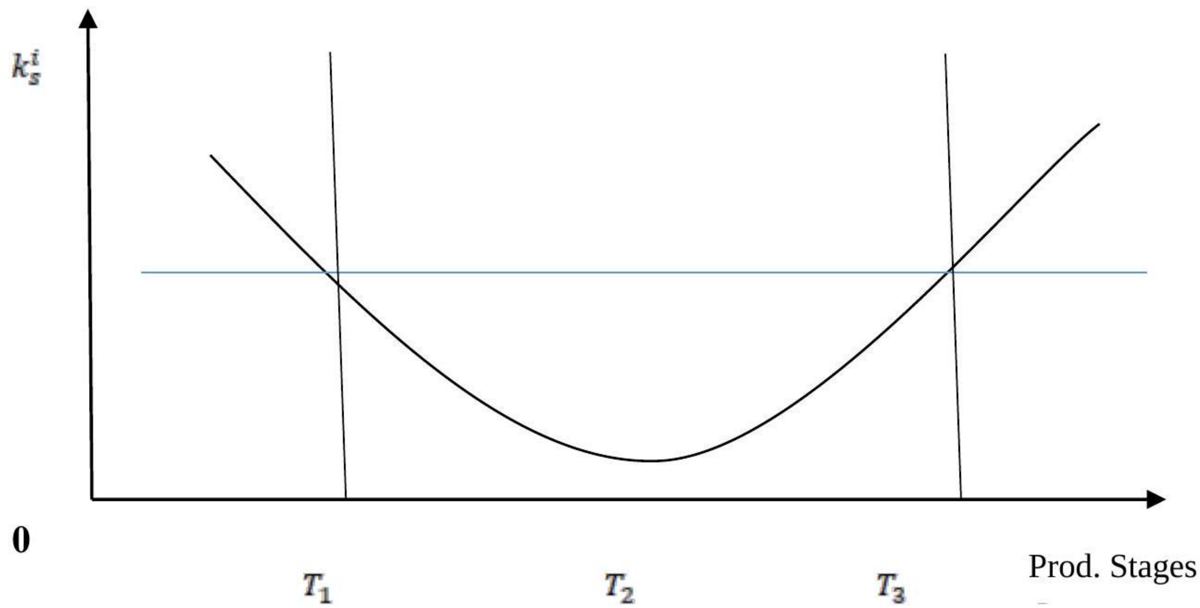
where the efficiency of production decreases with the length of time T_s such that $\frac{\partial A_s}{\partial T_s} < 0$ and increases with the capital deepening $\frac{\partial A_s}{\partial \alpha} > 0$, and The gains brought by the specialization in mechanical engineering will decrease as $\mathbf{T}$ increases $\frac{\partial^2 A_s}{\partial \alpha \partial T_s} < \mathbf{0}$. Substituting (A4) into (A1) and (A2), we can re-write the equilibrium condition into

$A^i\left(T_s, \alpha\right) h'\left(k_s^i; q_{-1}\right) = A^i\left(T_m, \alpha\right) h'\left(k_m^i; q_{-1}\right) = r$ where $s, m \in \{1, 2, 3\}$ for three stages

Based on equation (A4), we have the capital intensity of a particular stage of production to be written as $k_s^i = h'^{-1}\left(\frac{r}{A^i(T_m, a)}; q_{-1}\right)$. Since $A_{Ts}\left(T_s, \alpha\right) < 0$ and $h'(.) <.0$, we have k_s^i is decreasing with the length of task in the production stage, T_s. This result could be explained that: the longer period the production stage is (or the more task is involved in the stage of production), the farm is more willing to use labor to replace capital in the production process.

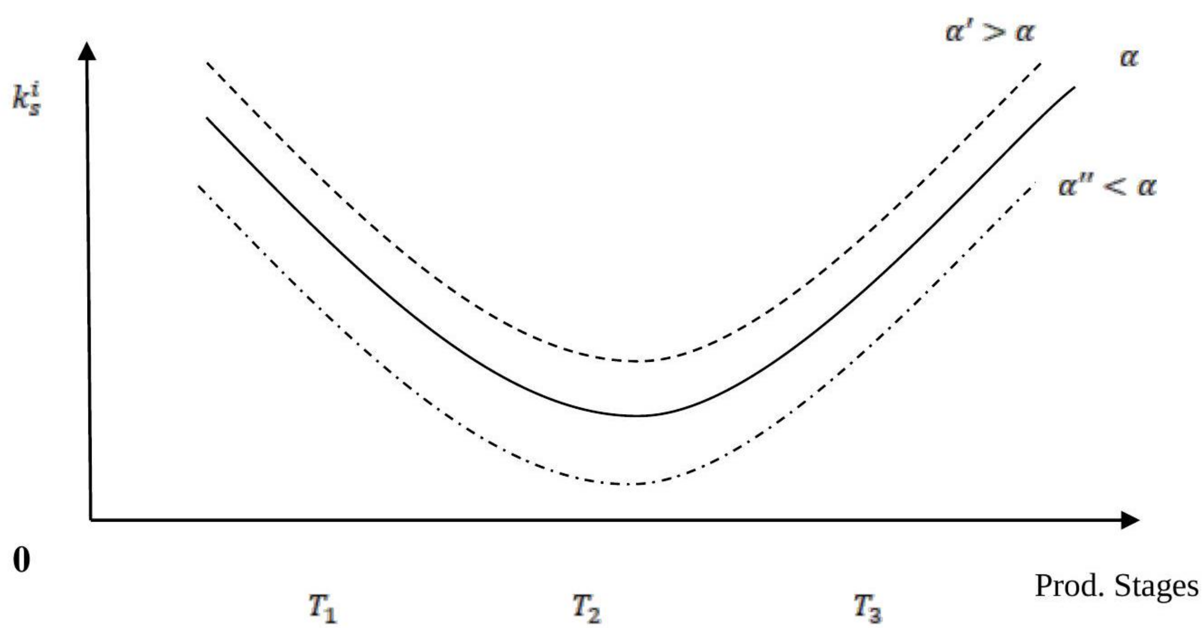
The above results could be further illustrated in Figure A1. The x-axis represents a continuous wheat production process comprising various tasks such as the ploughing/sowing, the plant protection (i.e. fertilizer, weed/pest control etc.), and the scale of x-axis represent the time length of the related tasks for each of the three stages. The y-axis represents capital intensities. Comparing with the ploughing/sowing and the harvesting stages, the plant protection stage will have more diversified tasks included and take much longer time and thus the capital-labor ratio for the plant protection stage would be lower than that for the other two stages. The phenomenon could also be explained as that farms are willing to use more labor (rather than capital) to cope with the relatively more complex production process when there is no strong time pressure.

Figure A1. Relationship between capital intensity and time length of tasks



Moreover, we know that capital deepening (or using more capital to replace labor) will tend to increase the efficiency of wheat production at all production stages, if other conditions hold constant. If farms can obtain capital input from a competitive market and all capital come from self-own investment, we have $\frac{\partial k_s^i}{\partial a} > 0$ because of the assumption of $\frac{\partial A_s}{\partial a} > 0$. This condition holds for all production stages. Combining this derivation with the impact of task-related work, we have the relationship between capital intensity and capital efficiency (α) and the length of tasks (T_s).

Figure A2. Impact of capital deepening on capital-intensity



A.2: Self-employed Investment vs. Mechanization Service

To take into account of mechanization service and its impact on wheat production in different stages, we assume that farms can choose to use either mechanization service or self-owned capital to replace labor in different stage of production. Comparing to self-owned capital, mechanization service is relatively cheaper in user costs but it may suffer from moral hazard, $\frac{\partial 2A_s}{\partial\epsilon\partial T_s} < 0$ or $\frac{\partial\epsilon^l}{\partial T_s} < 0$? Thus,

mechanization service and self-owned capital can be assigned with different capital efficiencies (or α), depending on the moral hazard levels (or the time length of tasks, T_s). Specifically, when

T_s is small, the advantage of mechanization service in saving user costs overwhelm its supervision costs due to potential moral hazards and thus capital efficiencies of mechanization services will be higher than self-employed capital, such that $\alpha^t > \alpha$. However, when T_s is large, the advantage of mechanization service in saving user costs cannot offset its supervision costs due to the potential moral hazards and thus capital efficiencies of mechanization services will be lower than self-employed capital, such that $\alpha' < \alpha$.

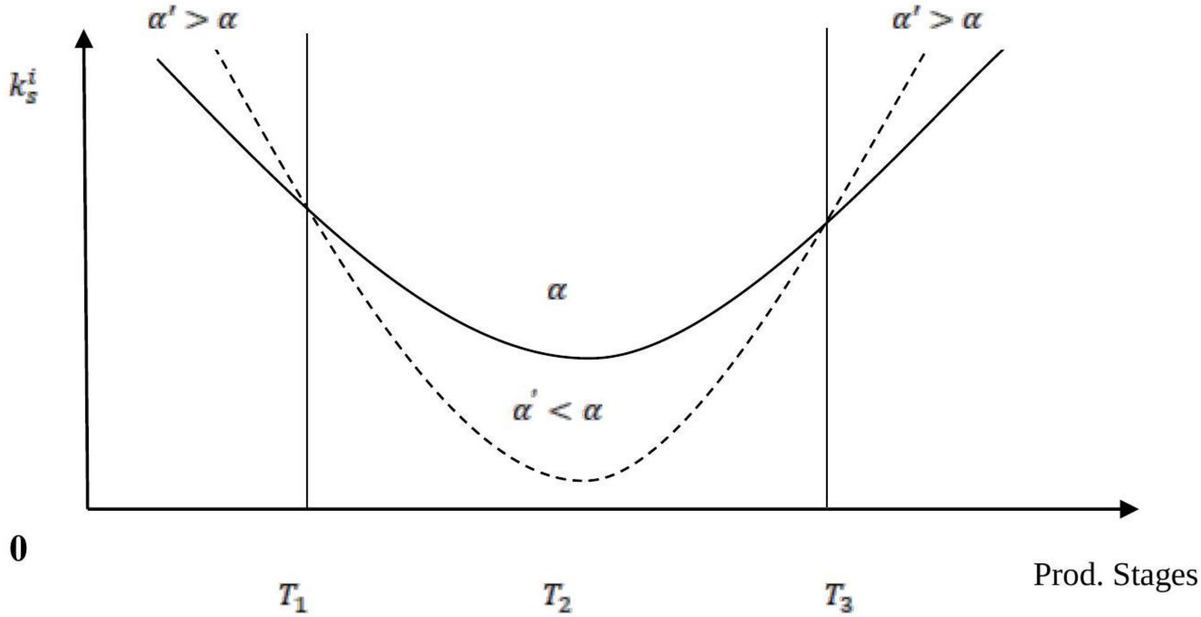
Applying this assumption about mechanization, we assume that α_m and α_s to denote different capital efficiency. Thus, using (5), we will have the relative capital-intensity between two stages of production could be written as:

$$\frac{k_s^i}{k_m^i} = \frac{h'^{-1}\left[\frac{r}{A^i(T_s;\alpha_s)'}; q_{-1}\right]}{h'^{-1}\left[\frac{r}{A^i(T_m\alpha_m)'}q_{-1}\right]}$$

where $h'() >.0$ and $h''() <.0$.

The above discussion about capital intensity in different stages of production can be further analyzed in Figure A3, where the x-axis represent the different production stages and the y-axis represents the capital intensity. The black solid line shows the relationship between capital intensity and the time length of tasks (T_s) when only self-employed investment is used (and α is fixed). Whereas, the dotted black line shows the relationship between capital intensity and the time length of tasks (T_s) when mechanization service is introduced. Although capital intensity decrease with T_s in the plant protection stage in both cases where mechanization services is allowed to be used or not, the capital intensity at different production stages exhibit different patterns. The finding can be used to generate a proposition.

Figure A3. Capital intensity change with mechanization service



Proposition 1: Mechanization level decreases when T_s increases. Mechanization level increases when α_s increases.

Proposition 2: Mechanization services increase capital intensity in the production stage of simple tasks (or small T_s), while decrease capital intensity in the production stage with complex tasks (or large T_s).

Proposition 2 provides an interesting explanation on the difference in capital intensities at different stage of wheat production, when mechanization service is introduced. Specifically, since the ploughing/sowing and harvesting stages involves simple and short tasks (with short T_s), mechanization service will increase capital efficiency and thus increase the by-stage capital intensity. However, the plant protection stage involves complex tasks (with long T_s), mechanization services may induce moral hazards and thus reduce capital efficiency and thus lower the by-stage capital intensity. As the by-stage productivity will increase with capital intensity which in turn will aggregate to the farm level, the asymmetric impact of mechanization service on capital intensity at different production stages may restrict further improvement of farm-level productivity.

Appendix B. A Detailed Discussion on Data Collection

The data used in this study come from a rural household survey of 240 wheat farms in Shandong and Henan provinces (which are the main producing areas of wheat and corn in China) for three rounds. The first round of the survey began in December 2013, the second and third rounds began in August 2016 and June 2021 respectively, with a focus on investigating the situation of wheat farmers growing wheat in 2013, 2015 and 2020. A random sampling strategy has been adopted. Specifically, we randomly selected three counties from the major wheat producing counties in Henan and Shandong provinces respectively. They include Lixin, Wenshang, Feicheng, Fengqiu, Yucheng and Linyi, which belong to 6 prefecture-level cities: Dezhou, Jining and Taian in Shandong and Xinxiang, Shangqiu and Luohe in Henan.

The surveyed areas use a cropping system of rotation between wheat and corn, with wheat sown in October, harvested the following June, followed immediately by corn sowing in June and harvesting in October. The survey was conducted through face-to-face household interviews by investigators, with each interview taking about 2 hours to complete. The questionnaires used in the three-year follow-up survey were the same, and their content covers basic information of the farmer's family members, land operation and crops, wheat production inputs and outputs etc. The investigators received strict training to ensure the effectiveness and reliability of conducting the interviews.

In the first round of surveys in 2013, 6 sample counties were selected, with sample towns in each county divided into two groups based on the degree of land transfer, with 1 sample town randomly selected from each group, 2 sample villages randomly selected from each town, and 10 households sampled from each village. Thus, a total of 240 wheat growers were sampled. In the second round of follow-up surveys in 2016, it was found that 52 of the 240 households could not be traced, mainly because they abandon agriculture and transferred their land to other farmers. In the third round of follow-up in 2021, only 145 out of the 188 targeted households were traced, mostly because of the urbanization process. See Table B1 for details of the sample tracking over time.

To understand the input-output relationship of wheat production, the research team asked each wheat farmer to randomly select two plots from all the wheat plots he operated in the first round of survey, and the investigators recorded the detailed input and output information for the two plots. In the second and third round of follow-up surveys, we basically traced the same plots. If the farmer was no
longer cultivating the selected plots, new plots were randomly selected from the same farm to ultimately supplement two plots.

In the questionnaire, the wheat production process was divided into 6 production stages by categorizing the related activities: plowing/land prepare, sowing/seedling, fertilizing, weeding/applying pesticides, irrigation, and harvesting. The investigators recorded wheat yield, labor input, mechanical input and material input at each production stage. Labor input was divided into family labor and hired labor; mechanical input was divided into farmers' own machinery and purchased mechanization services; material inputs included seeds, fertilizers and pesticides. Labor input was defined as the sum of labor input by family members, hired workers, and the supervision costs. Capital input was defined as the sum of the costs of own machinery and the cost of purchasing mechanization services. The cost of own machinery was defined as depreciation costs plus fuel costs of using own machinery. All capital and material inputs are first estimated by using the current price, and then adjusted for inflation using the corresponding price indexes (i.e. the price indexes for seed, fertilizer, pesticide, irrigation, capital and land rental etc.). The real measure of capital and material inputs are estimated using the 2015 constant price.

To capture the maximization decision of farmers, we add up all inputs and outputs (obtained from the plot level) to the farmer level. Specifically, the calculation method is: in 2013 and 2015, the arithmetic average value of the randomly selected two plots by farmers is converted into inputs and outputs per unit area of "mu", and then multiplied by the total area cultivated by farmers to calculate the total inputs and outputs at the farmer level; In 2020 , the inputs and outputs per unit area of "mu" reported directly by farmers were converted to farmer-level inputs and outputs by multiplying the total area cultivated by farmers of wheat.

During the survey process, we also found that the degree of mechanization of plowing land and sowing wheat for farmers (more than 90%) and the proportion of the use of mechanization are similar, which indicates that the operation methods of these two types of activities are basically consistent. At the same time, the plowing land and sowing operations are closely related in work time, and some farmers are accustomed to sowing immediately after plowing the land, and the two production links are carried out simultaneously. Therefore, in this study, we combine the plowing land and sowing stages into one and treat it as the first stage. The operation methods of fertilizing, weeding, spraying pesticides and irrigation are similar, mainly relying on labor and may need to be repeated multiple times, with an overall mechanization rate of less than 30%. We therefore classify these activities into the second stage, i.e. the growth protection stage. The degree of mechanization of the final harvest stage is close to 100% again, different from the plant protection stage. Therefore, we define the harvest stage as the third stage. The labor, capital and material inputs for the entire production process are the sum of the respective inputs for all production stages. The labor, capital and material inputs for the three stages of production are the total of the corresponding inputs included in each stage. For example, the labor input for the first stage is the sum of the labor inputs for the plowing land and sowing stages. The material inputs for the second stage are the sum of fertilizer costs, pesticide costs and irrigation costs for fertilizing, weeding, pesticide application and irrigation. Farmers' total output for the third stage is farmers' average yield multiplied by the total sowing area, and the calculation method for output for the first stage and the second stage is introduced in Section Three, paragraph five of the main text. In addition to labor costs, capital and material costs, the specific definition of the land value variable is described in Appendix C.

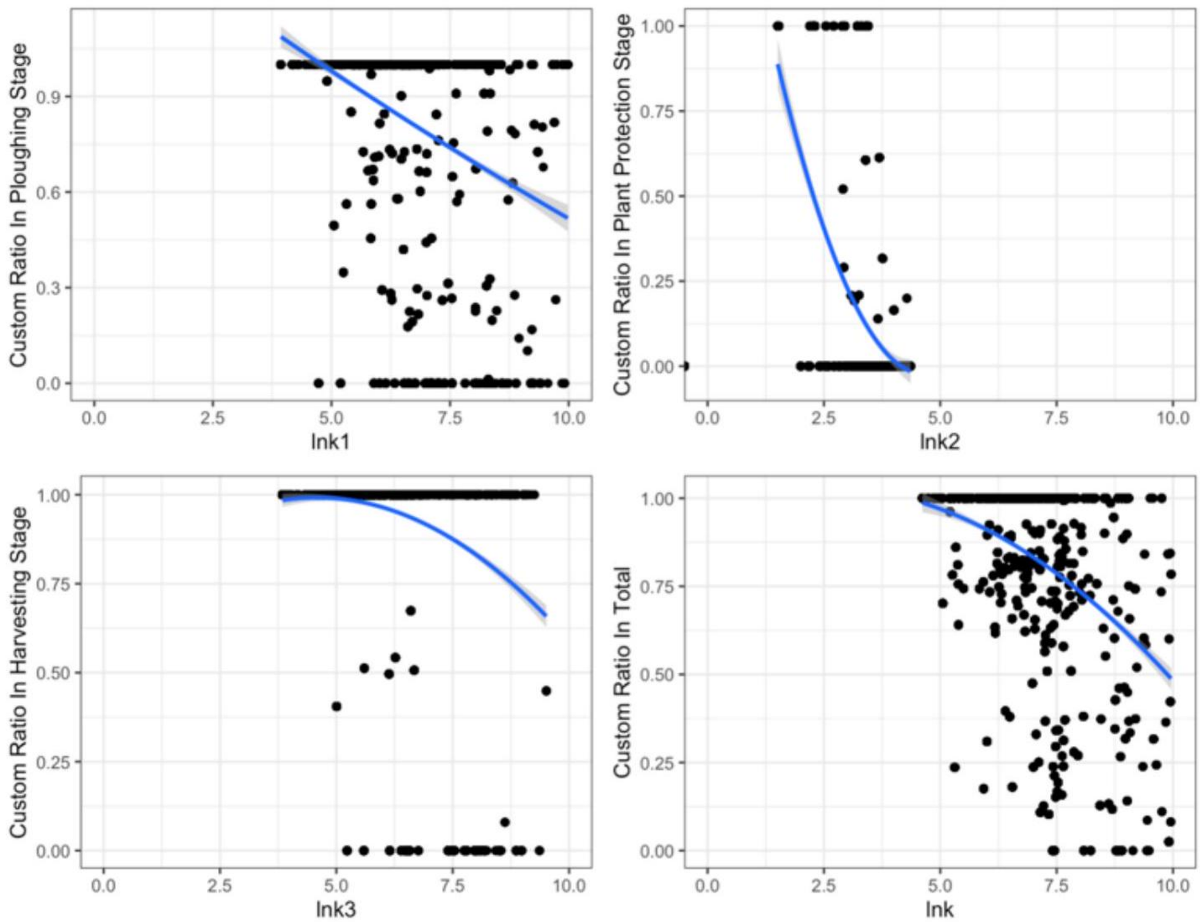
Table B1. Definitions of all variables used in this study

Variables	Definitions
Wheat yield (ton)	Maize yield per household (ton/household)
Wheat yield index at stage 1	Maize yield per household in ploughing/sowing stage (ton/household)
Wheat yield index at stage 2	Maize yield per household in plant protection stage (ton/household)
The plant index at stage 1	The plant index per household in ploughing/sowing stage (ton/household)
The plant index at stage 2	The plant index per household in plant protection stage (ton/household)
Capital intensity (yuan/household)	Total capital use in production per household (yuan/household)
Ploughing/Sowing stage	Total capital use in ploughing/sowing stage per household (yuan/household)
Plant protection stage	Total capital use in plant protection stage per household (yuan/household)
Harvesting stage	Total capital use in harvest stage per household (yuan/household)
Labor intensity (hour/household)	Total labor use in production per household (yuan/household)
Ploughing/Sowing stage	Total labor use in ploughing/sowing stage per household (yuan/household)
Plant protection stage	Total labor use in plant protection stage per household (yuan/household)
Harvesting stage	Total labor use in harvest stage per household (yuan/household)

Table B1. Definitions of all variables used in this study (Continued)

Variables	Definitions
Land value (yuan/household)	The total land value of the household (yuan/household)
Seed cost (yuan/household)	Total seed input in production per household(yuan/household)
Material cost in plant protection stage (yuan/household)	Total material input in production including fertilizer, pesticide, film and water per household(yuan/household)
Total TFP	The total factor productivity per household
Ploughing/Sowing stage	The total factor productivity in ploughing/sowing stage per household
Plant protection stage	The total factor productivity in plant protection stage per household
Harvesting stage	The total factor productivity in harvest stage per household

Figure B1 The relationship between capital intensity and mechanization service ratio



Note: The x-axis represents capital intensity, measured by log(k). The y-axis represents the ratio of mechanization services, measured by the proportion of mechanization service capital to total capital. The fitting line is created using a LOESS (Locally Estimated Scatterplot Smoothing) method.

Figure B1 shows that with the increased use of capital input, the proportion of mechanization services decreased gradually in all three production stages as well as in the entire production process. The horizontal axis represents the logarithmic total amount of capital inputs in each stage and at the farm level, and the vertical axis represents the proportion of mechanization services in the total capital use. This indicates that when users choose to increase the use of capital inputs, farmers tend to purchase machinery by themselves. This is mainly because the fixed costs of mechanization services are lower, but the marginal cost for farmers to use machinery services is higher. When farmers need to use a large amount of capital, it is cost-effective for farmers to purchase machinery themselves.

Appendix C. Land Hedonic

In this paper, we use the hedonic approach to estimate the land input, so as to eliminate the impact of land quality across farms on agricultural output (or productivity). To estimate land value in 2013, 2015 and 2020, we first calculate the land rental price of the village where the farmer is located in 2015 at constant prices, and use it to multiply the wheat sowing area of the farmer. We use a mixed OLS regression of the land rental on the land characteristics including nitrogen content of the plot land, organic carbon content of the land, number of plots per unit area and the average distance of all wheat plots from the farmer's house for that household, with all variables taking natural logarithm. The fitted value of the farmer's total land rental calculated after the regression is used as the variable "Land input" of the farmer's land value. See Table C2 for the specific regression results of land prices.

Appendix C1. Multivariate analysis of land price (Yuan).

Variable	**Coefficient (t-ratio)**
Dependent variable: Price of land of wheat (Yuan/household)	
Total nitrogen content of land (g/kg)	2.42**
	(2.19)
Total organic carbon content of land (g/kg)	1.70
	(1.46)
Land fragmentation (plot/ha)	-1.20***
	(32.93)
Distance of the home to the plots (km)	-0.04
	(0.85)
Time trend dummy (2015)	-0.79***
	(8.88)
Time trend dummy (2020)	-0.42***
	(4.78)
Township dummy	Yes
Constant	-11.82
	(1.38)
Observations	435
R^2	0.815

Note: Absolute values of t-ratio in parentheses. The variables takes the logarithm. *,**,***indicates statistically significant at the 10%,5%,and 1%,respective.The number of observation is 435.

Appendix D. Estimation of Multiple-stage Production Function

Our first-step estimating farm TFP for each production stage is then given by the following equation, in which stage-specific output y is expressed as a semiparametric function of $(k_{ist}, l_{ist}, e_{ist}, r_{ist})$ and of the information of downstream stages in the case of the plowing/sowing stage (stage 1) and the plant protection stage (stage 2):

$$Y_{ist} = \alpha_s l_{ist} + \beta_s k_{sjt} + \gamma_s r_{ist} + \varphi^{-1}\left(l_{ist}, k_{ist}, r_{ist}, e_{ist}\right) + \varepsilon_{sjt} \tag{D1}$$

As usual, we collect the deterministic terms and denote them as

$$\phi_{ist} = \alpha_s l_{ist} + \beta_s k_{sjt} + \gamma_s r_{ist} + \varphi^{-1}\left(l_{ist}, k_{ist}, r_{ist}, e_{ist}\right) \tag{D2}$$

In literature, it is argued that the adjustment of capital and labor input use by farmers will take longer time than that of intermediate inputs, such as seeds, fertilizers and chemicals. This is not only because the unit cost of intermediate inputs is much lower than capital and labor input for small holder farms, but also because intermediate inputs are more divisible. Given wheat farmers' practice, it is reasonable to assume that the demand for intermediate inputs depends on productivity and the predetermined capital and labor input.

The advantage of using aggregate intermediate inputs as control variable lies in two-fold: first, intermediate inputs, though different in each stage of production, is measured in terms of money metric in real term, which addresses the issue of potential bias resulting from quality differences in inputs; and second, using intermediate inputs for the control functions throughout all the three stages of production make our by-stage estimation more consistent with each other.

We approximate $\phi_{\text{ist}}(.)$ by a high order polynomial and use OLS regression for estimation, with$the control of time dummies (D_t)$ and regional dummies (D_r) in the regression to account for time-variant and time-invariant external shocks. Quality adjustment has been made for capital and labor, as well as the aggregate intermediate inputs, using their corresponding price as the hedonic weights.

Our second step is to estimate the parameters $\theta = (\alpha, \beta, \gamma)$ by GMM, which exploits a Markov assumption on farms' TFP and the timing of input choices and sita denotes the parameter space. In particular, we assume that farm productivity in stage stage s follows a first-order Markov process:

$$w_{ist} = g\left(w_{is,t-1}\right) + \xi_{ist} \tag{D3}$$

which says that the current productivity shock consists of an expected term predicted by productivity at $g\left(w_{is,t-1}\right)$ plus a deviation from the expectation, often referred to as the "innovation" component ξ_{sjst} . Note that w_sjst is identified up to sita from the first step after taking out measurement error and unanticipated shocks from output. We regress w_{ist} on a linear function of $w_{is,t-1}$ to obtain $g\left(w_{is,t-1}\right)$. Denote

$$w_{ist}(\theta) = \phi_{ist}(.) - \alpha_s l_{ist} - \beta_s k_{ist} - \gamma_s r_{ist} \tag{D4}$$

For a given θ, g$(.) canbeestimatedandthus \xi_{\text{ist}}$ is obtained. The latter is used to construct the moment conditions:

$$E\left[\left(\xi_{ist}(\theta) + \epsilon_{ist}\right)\begin{pmatrix} l_{is,t-1} \\ l_{ist} \\ k_{ist} \\ r_{is,t-1} \\ n_{it} \\ \Phi_{i,t-1}\left(k_{is,t-1}, l_{is,t-1}, r_{is,t-1}, n_{it}\right) \end{pmatrix}\right] = 0 \tag{D5}$$

Since capital input is a state variable at t, it should be orthogonal to the innovation shock on productivity at t. We use current labor (l_{sjt}) as an instrument for itself because of its dynamic feature, and also include labor at $t-1$ as an additional instrument. And, we use lagged material input $\boldsymbol{r}_{sj,t-1}$ as an instrument for $\boldsymbol{r}_{sjt^*}$ As is pointed out by Gandhi et al. (2020), the use of $\xi_{sjt} + \varepsilon_{sjt}$ rather than ξ_{sjt} alone in the moment condition is more general. We search over the parameter space sita to find alpha_hat, beta_hat and gamma_hat that minimize the above moment conditions.

We use the GMM procedure to identify separately production function coefficients for each stage s in a backward order as described above, $s = 3, 2, 1$. As is mentioned, we allow the status of second stage and the share of secondary refining to enter the productivity evolution process since the technology in the plant protection stage may potentially affect the law of motion of productivity.

Appendix E. Estimate the NDVI index for the by-stage output

The Normalized Difference Vegetation Index (NDVI) serves as a widely recognized index for vegetation monitoring. Its foundational principle capitalizes on the distinct reflective properties of vegetation leaves in the near-infrared and red light spectrum. The NDVI is calculated using the formula:

$$\frac{NIR - RED}{NIR + RED} \tag{E1}$$

A ratio normalized design that mitigates the effects of solar zenith angles and surface reflectance intensity, ensuring inherent stability. The NDVI values range between -1 and 1 , with higher values indicating richer vegetation coverage. A salient feature of NDVI is its commendable cross-sensor and spatiotemporal comparability, facilitating comparisons across different regions and time frames.

We use Landsat 8 SR imagery in Google Earth Engine Platform. NDVI can be influenced by external factors such as atmospheric effects and surface background effects. To minimize these influences, the Landsat 8 SR imagery do corrections in the following ways:

- Atmospheric Correction: Leveraged the LaSRC model to correct surface reflectance atmospherically, reducing the impact of aerosols and water vapor.
- Orthorectification: The imagery was orthorectified to align with a standard map projection coordinate system.
- Surface Temperature Correction: Employed the single-channel algorithm developed by RIT, NASA, and JPL to compute surface temperatures from the TIR band.
- NDVI Temporal Adjustment: Utilized the ASTER NDVI product to temporally adjust the ASTER GED, enabling the computation of surface temperatures for the target Landsat scenes.
- Cloud Masking: The Fmask algorithm was employed to mask clouds and potential cloud shadow areas.
- Scene Stitching: Overlapping areas were stitched together to produce a standard scene of approximately 170 km $\times$ 183 km.
- Known Errors: Errors related to cloud and cloud shadow-associated surface temperature retrievals were acknowledged.

Detailed process

(1) Calculated the maximum NDVI values during the sowing and plant protection periods using the Landsat 8 SR satellite data segmented by time.

(2) High-resolution remote sensing map layers were loaded for the plots where wheat was cultivated by farmers in 2013, 2015, and 2020. These plots were GPS-located, and their positions and shapes were delineated on the map.

(3) Using the plots as masks, the NDVI satellite data was cropped, and a summation operation was performed on the resulting NDVI grid values.

(4) At the farmer level, the NDVI grid values of all plots were aggregated.

(5) A linear regression approach was adopted to estimate the final yield in relation to the NDVI during the plant protection and sowing phases, recursively generating y_1 and y_2.

Figure E1: Changes in Land Parcels and NDVI for Farmer(No. 512203) from 2013-2020

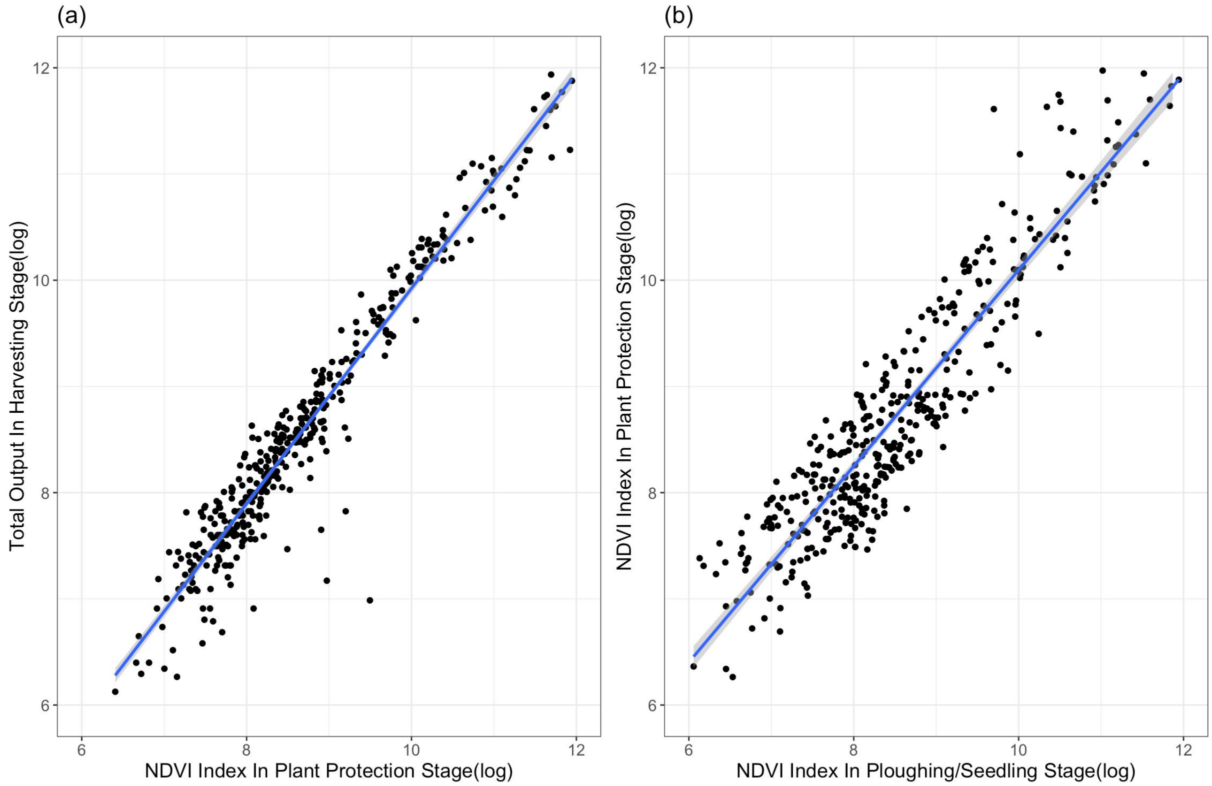
(a) 2013

(b)2015

(c)2020

Note: The bounds of plots are from Farmer(No. 512203) in our survey. The figure is computed using the Google Earth Engine (GEE) platform. The color represents the Normalized Difference Vegetation Index (NDVI), specifically the maximum NDVI during the crop protection phase, calculated based on Landsat satellite data. This figure demonstrates our capability to track the changes in each land parcel for individual farmers.

Figure E2. Relationship of log outputs in different stages



Note: Panel (a) represents the relationship of log(NDVI) and log(real output) between plant protection and harvesting. Panel (b) represents the relationship of log(NDVI) between seedling and plant protection.