Market Failures, Factor Allocation and Input Use in Chinese Agriculture

Minjie Chen

Propositions

1. Machinery services reduce factor misallocation in a smallholder production system.
   (this thesis)

2. Chemical fertilizer sellers are a major cause of the persistent fertilizer overuse in China.
   (this thesis)

3. Adaptation to climate change, not mitigation, will save humankind in the long run.

4. Urban prosperity is a prerequisite for long-term rural development.

5. While natural scientists prefer to build new blocks, social scientists prefer to replace old ones.

6. The science of economics is becoming the science fiction of economics.

7. Doing a PhD is like hiking in the wilderness: beautiful ‘sceneries’ slow you down.

8. Digitalization is the best adaptation to a pandemic.

Propositions belonging to the thesis, entitled

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To my family

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CHAPTER 1
GENERAL INTRODUCTION

1.1. PROBLEM STATEMENT

One of the striking characteristics of agriculture in many less developed countries, particularly those in the sub-Saharan region and South and East Asia, is that the operational farm sizes are often very small and distributed relatively equally across producers. In recent efforts to understand aggregate agricultural productivity, this characteristic of farm size distribution has been directly linked to misallocation of agricultural land, that is, the most productive farms are not cultivating more land (see for example Adamopoulos and Restuccia, 2014). The literature often attributes the cause of this misallocation to land market frictions that are prevalent in these countries, such as unsecured land property rights and imperfect markets of land rentals and land sales. Small farm sizes have also been indirectly linked to the misallocation of capital and labor because smallholders can face greater challenges than larger farm operators in collateralizing their land for capital investment, labor hiring, and in reallocating family labor from agriculture to non-agricultural sectors (see Lagakos and Waugh, 2013; Gollin et al., 2014; Restuccia and Rogerson, 2017; Adamopoulos et al., 2020). The large extent of factor misallocation can imply a substantial loss in aggregate agricultural productivity, which further explains a large part of the low standards of living among the poorest agricultural countries.

The agricultural sector of China falls largely into this broader context. Agricultural production in the country has long been dominated by smallholders since the implementation of the Household Responsibility System[1] in the late 1970s. Under this system, the agricultural land is owned by the village collectives and land use rights are assigned, often on an egalitarian basis, to each farming household by the village collectives (i.e., land contraction). Recent official data shows that more than 90% of crop producers operate a farm size of less than one hectare (NBS, 2016). The situation seems to have not been improved much over a decade, even though policies favoring farm size expansion were implemented and even though there was an emerging class of middle-sized and large-sized farms run by families, cooperatives, and agribusinesses (see NBS, 2006; Ji et al., 2016). Although farmers are allowed and even encouraged to transfer their contracted land to other farming entities in the land rental market, land collateralization for credit is still difficult due to small farm sizes and the absence of land sales market. These characteristics seem

[1] This system has transformed China from collective farming into individual farming and has lifted hundreds of millions of (rural) households out of poverty in China, and it is considered as the basis for further economic growth in China.

to imply that there is a large misallocation not only in land, but also in capital. Findings for Chinese agriculture in the recent literature support this: the estimated gains in aggregate agricultural productivity are substantial and can be up to 136% if factors were efficiently allocated across farms (see Gai et al., 2017; Adamopoulos et al., 2020; Chari et al., 2021). However, as will be argued in this thesis, the current literature on factor allocation may have missed some important characteristics of Chinese agriculture and can lead to overestimation of factor misallocation and overemphasis on efficiency gains while ignoring equity issues.

Besides the problem of potential factor misallocation among smallholders, small-sized farming brings additional challenges to Chinese agriculture. Recent evidence on environmental externalities indicates that the intensity of chemical fertilizer use declines with farm size enlargement, i.e., small farms are found to be associated with more fertilizer use per unit of land (see for example Ju et al., 2016; Wu et al., 2018). In the broader context of persistent overuse of fertilizers in China, such evidence implies that smallholders are not only producing with suboptimal productivities, but are also facing greater environmental pressure. To increase productivity and achieve sustainable agricultural development, the government and relevant research institutes initiated various types of policies and programs to help farmers reduce the intensity of fertilizer use (see for example Zhang et al., 2013; MOA, 2015; Cui et al., 2018). However, the intensity of micro-level chemical fertilizer use (on a per unit of land basis) is not declining even in very recent times (NDRC, 2011, 2018, 2019), although promising achievements have been made at aggregate level.

The above observations of the Chinese agriculture raise two broad questions: First, are productive factors truly severely misallocated across farms, as the literature suggests? If not, what are the potential factors contributing to the overestimated misallocations of factors in previous studies? If productive factors are less misallocated, then what will a tenure-security-enhancing land certification program imply for factor allocation and agricultural household welfare? Second, why do government efforts to reduce the intensity of chemical fertilizer use appear to have limited effects? In addition to the driving factors from the farmers' side, what else may lead to the persistently high use intensities of chemical fertilizer in China? To answer these questions, this thesis will take a step back and examine what might have been missed in the literature for understanding resource misallocation and excessive fertilizer use in the agricultural sector of China. The main objective of doing so is to obtain an improved understanding of market failures that contribute to misallocation of factors and excessive fertilizer use in Chinese agriculture.

To achieve this objective, I first review the literature to understand the status of resource misallocation studies in agriculture, to sort out the main approaches used for theoretical and empirical studies, and to identify potential research gaps in the current literature. Following that, I investigate whether resource misallocation in China's agricultural sector has been overestimated by considering the role of hired machinery services in a regional study. Then I examine whether the recent tenure-security-enhancing land certification program facilitates the reallocation of factor inputs, including land and labor toward more productive units and activities. Along with that, I also study the welfare effect of the program by estimating its impact on intra-village income inequality. In the latter part of this thesis, I turn to explore the input use behavior of smallholders in China, by particularly looking at whether and how local fertilizer sellers influence farmers' fertilizer use intensity. These tasks are reflected in the following four research questions:

1. What is the status of the literature on resource misallocation studies in the agricultural sector, what are the research methodologies, and what are the potential knowledge gaps in the current literature?
2. Are productive factors severely misallocated across farms in the agricultural sector of China, even if the recent trend of hired machinery services has been taken into account in regional study?
3. Does the recent land certification program facilitate land reallocation across farms and labor reallocation across agricultural and non-agricultural sectors? And, what is the impact of the program on intra-village cross-household income inequality?
4. Do sellers in China's local fertilizer market influence farmers' fertilizer use intensity? If so, what is the potential mechanism?

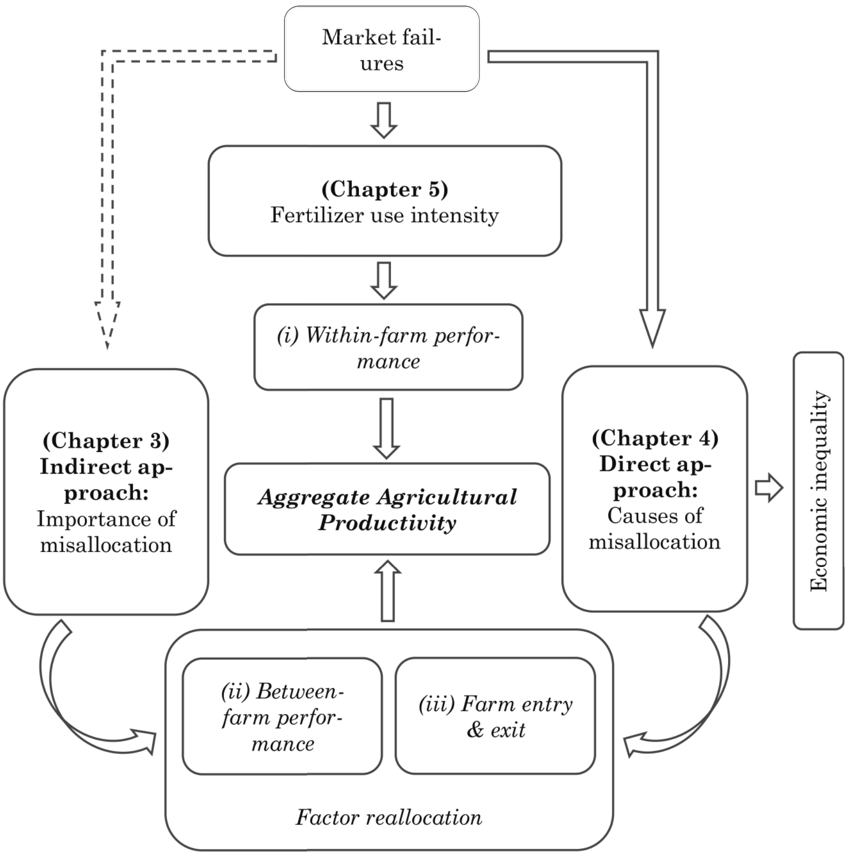
Each of these research questions will be answered independently in a separate chapter of this thesis, with distinctive theoretical models and empirical strategies tailored to each of them. In the following sections, I briefly discuss the conceptual framework, and then overview and synthesize research materials and methods that I use to answer them.

1.2. CONCEPTUAL FRAMEWORK

Aggregate agricultural productivity at the macro level is simply a weighted average of individual farm productivities at the micro level. In the population distribution of farm-level productivities, the improvement in aggregate agricultural productivity can be decomposed mechanically into three channels (see Cusolito and Manoley, 2018; Fuglie et al., 2020): (*i*) the improvement in within-farm performance (e.g., existing farms improve their own productivity through technological upgrades); (*ii*) the improvement in between-farm resource allocation among existing farms (i.e., resources flow from lower productive farms to higher productive farms); and (*iii*) the entry and exit of farms with heterogeneous productivities in the agricultural sector (i.e., lower productive farms exit from and higher productive farms enter into agricultural production). Farm entry and exit can be considered as a special case of the reallocation of resources between farms, in which the resource of exit farms goes to zero and entry farms obtain resources from various types of reallocations (see Restuccia and Rogerson, 2017). This decomposition is illustrated in items (*i*), (*ii*) and (*iii*) in *italics* in Figure 1.1 below.

The study of resource misallocation mainly involves examining what is happening in channels (*ii*) and (*iii*), that is, the reallocation of resources between farms and farm entry and exit. The most applied research methodologies for factor misallocation analyses in the agricultural sector can be summarized by two approaches: the indirect approach, which emphasizes quantifying the importance of factor misallocation, and the direct approach, which emphasizes understanding the specific sources of factor misallocation (see Chapter 2). The natural starting point is the indirect approach that aims to quantify to what extent the productive factors are misallocated among a studied group of farms, without identifying the market failures that cause such misallocation, that is, the market failures are implicitly embedded in the analysis (the dashed arrow in Figure 1.1). The theoretical background for such a quantification is that, under the assumption of homogenous input prices, the efficient allocation of a productive factor requires its marginal (revenue) product to be equated across farms that are heterogeneous in their productivities. Following this, the

Figure 1.1. Conceptual framework



researcher may examine, for example, the cross-sectional distribution of marginal products across farms, and any measured dispersions from the distribution would potentially imply factor misallocation and loss in aggregate agricultural productivity (see Chapter 2 and Chapter 3).

On the other hand, instead of quantifying the misallocation, the researcher may want to circumvent the making of structural assumptions in the indirect approach and is more interested in directly identifying the potential market failures that cause factor misallocation. The purpose is usually to assess the impact of public policies or to make recommendation for policy makers to design institutions to reduce market frictions and increase the efficiency of factor allocation. However, efficiency gains may be related to losses in equality and, therefore, this requires that additional attention be paid to the impact assessment of agricultural productivity policies (see Chapter 4). Although factor reallocation may be important, Figure 1.1. shows that it is not the only way to increase aggregate agricultural productivity. Efficient input use also matters through the channel of within-farm performance. If there are market failures to distort the efficient use of production inputs, then farms would produce with suboptimal productivities, which may not only lead to lower aggregate agricultural productivity, but also to negative environmental externalities if the relevant input is agrochemical (see Chapter 5).

1.3. MATERIALS AND METHODS

To carry out the specific research work as described in the above conceptual framework, in this section I summarize the research materials and methods that will be used throughout this thesis. It is important to note that, since Chapter 2 reviews the relevant literature, my discussion of the materials and methods will focus on the research questions asked in Chapters 3 – 5.

1.3.1. DATA

The data source for this thesis mainly involves two first-hand household-level survey data sets that I collected, in cooperation with other researchers. In particular, one data set was collected from field work in the prefecture of Handan, Hebei Province, in early 2018. We sampled and interviewed more than 2,000 farming households from 135 villages in four counties of Handan prefecture using a multistage cluster sampling approach (more details are provided in Chapter 3). The main information collected in this data set includes household roster information, assets, and very detailed agricultural input and output information. I use this data set in Chapter 3 to quantify the extent of factor misallocation in the sample.

The other major data set was collected from field work in three provinces in early 2019, i.e., Liaoning, Jiangsu, and Jiangxi, and again by cooperating with other researchers. The field work sampled and surveyed 1,440 households in 120 villages, using a multistage cluster-stratification sampling method (see both Chapters 4 and 5 for more details). These villages are located in six counties, two in each province. This data set contains information of household rosters, agricultural input and output with details on agricultural land and agrochemical uses, household income and expenditure, risk and time preferences, etc. This data set is used in Chapter 4 to study the impact of land certification program on the reallocation of land and labor, and on intra-village income inequality. It is also used in Chapter 5 to study the influence of fertilizer sellers on the intensity of fertilizer use by farmers.

In addition to the above two household-level data sets, the village-level data sets that were collected in the villages where we conducted the household surveys are also used. They are either applied directly to perform village-level empirical analyses or used to control for village-specific effects.

1.3.2. METHODS

The main research method used for the thesis is a combination of literature review, analytical modeling, and econometric estimation. Specifically, in Chapter 2, I first review the recent literature that studies micro-level data to understand factor misallocation in the agricultural sector and its implications for aggregate agricultural productivity. The defining scope of misallocation in the review is narrow and simple: it specifically means the misallocation of productive inputs such as land, capital, labor, and intermediate inputs across farms that produce homogeneous agricultural goods. Given this definition, I follow the general structure of Restuccia and Rogerson (2017) and organize the review into two broad categories. The first category is denoted as using an indirect approach, as it studies the importance of factor misallocation in various contexts. The second category is denoted as using a direct approach, as it identifies the specific sources of factor misallocation. Finally, I also pose a few questions for potential future studies.

Closely related to the structure of the literature review in Chapter 2, Chapters 3 and 4 use the indirect and direct approaches, respectively, to study factor allocation issues in the agricultural sector of China. In particular, Chapter 3 quantifies the importance of factor misallocation in understanding aggregate agricultural productivity in Chinese agriculture. It derives the static efficient allocation of factor inputs in a quantitative framework characterized by heterogeneous farms, decreasing returns to scale production function at the farm level, and a social planner that maximizes total output given total resource endowments and heterogeneous farm-level productivities. Then the chapter empirically examines to what extent land and capital are misallocated in a region of the North China Plain that is characterized by small and relatively equally distributed farm sizes and active use of hired machinery services, using the Handan data set.

Chapter 4 complements Chapter 3 by using the direct approach to examine the cause of potential factor misallocation, without explicitly linking to agricultural productivity. It attempts to estimate the impact of a recent land certification program on the decisions of rural households on land rentals and migration, as well as on intra-village income inequality. Using the three-province data, it measures the village-level key explanatory variable in terms of how many years the land certification program had been completed in a village. The purpose of doing so is to capture the impact of the program over time. The analysis also adds in a quadratic term to capture the potential non-linear effect of the program on the outcomes of interest.

Chapter 5 focuses on a specific type of intermediate input – chemical fertilizer. Although it does not explicitly measure the misallocation of this intermediate input across farms, it studies information frictions in the chemical fertilizer market by questioning whether the high intensity of chemical fertilizer use by Chinese farmers is related to sources providing information on fertilizer use. The particular focus of this chapter is on the role of fertilizer sellers. It argues that chemical fertilizer is a credence good for which *ex post* detection of excessive use is costly for local farmers. Based on this concept, the chapter use the three-province data to empirically test whether and to what extent rice farmers' fertilizer use intensities are related to the sources from which they learn about how much fertilizer is needed. The study controls for household and land characteristics in the estimation.

1.4. OUTLINE

This thesis is organized as follows: Chapter 2 reviews the recent literature that studies factor misallocation in the agricultural sector. Building on the structure of the literature review, Chapter 3 quantifies the extent of factor misallocation in a region in the North China Plain using farm-level data. Chapter 4 assesses the impact of a recent land certification program on various economic outcomes in rural China. Chapter 5 focuses on examining the influence of different information sources, particularly the fertilizer sellers, on farmers' chemical fertilizer use intensity. The thesis concludes in Chapter 6 by synthesizing the findings in Chapters 2 – 5 and discussing how these findings contribute to the broad literature, along with these findings' limitations.

CHAPTER 2

RESOURCE MISALLOCATION IN THE AGRICULTURAL SECTOR: A REVIEW OF MICRO-LEVEL EVIDENCE

ABSTRACT This chapter reviews the recent literature that studies micro-level data to understand factor misallocation in the agricultural sector and its implications for aggregate agricultural productivity, both within China and beyond. The defining scope of misallocation in this review is narrow and simple: it specifically means the misallocation of productive inputs such as land, capital, labor, and intermediate inputs across farms that are heterogeneous in their productivities and produce homogeneous agricultural goods. Following the spirit of Restuccia and Rogerson (2017), the review organizes the literature into two broad categories: (*i*) the studies that use structural models to quantify the importance of factor misallocation in various contexts (denoted as the indirect approach), and (*ii*) the studies that attempt to identify the specific sources of factor misallocation in similar contexts (denoted as the direct approach). Following the structured review of the relevant literature, it closes by laying out a few questions for potential future studies.

2.1. INTRODUCTION

The majority of poor countries rely on agriculture as a means to survive, and therefore the improvement of aggregate agricultural productivity is vital for poverty reduction, structural transformation, and overall economic development in these countries. However, recent empirical studies have documented a trend of global decline in productivity growth, especially in the manufacturing sector (Cusolito and Maloney, 2018). Similar evidence has also been found for the agricultural sector. For example, recent studies focusing on China have found that the growth rate of aggregate agricultural productivity is declining in recent years (Gong, 2018, Sheng et al., 2020). Moreover, agricultural productivity growth in China, as well as in other countries, also faces increasing environmental challenges, for instance, from the overuse of agrochemicals and climate change. These cast doubts on the sustainability of agricultural production. Agricultural development seems to be increasingly dependent on improved productivity. Therefore, how to refuel the productivity growth engine in agriculture becomes especially important for poor countries. The key question is: How could these countries improve their aggregate agricultural productivities? The general answer to this question may be obtained from two distinctive frameworks: one is at the macro level, and the other is at the micro level.

At the macro level, the convention is to assume an aggregate production function and fitting the implied empirical models with aggregate data at the regional or country level to test important hypotheses and propose policy recommendations. However, this is theoretically challenged regarding the validity of aggregate production functions. For example, Banerjee and Duflo (2005) document that there is enormous heterogeneity of rates of return to the same factor even within a single economy, indicating resources are not allocated optimally across productive units. This fact threatens the existence of a neoclassical aggregate production function that embeds or assumes optimal resource allocation. Empirically, the criticism questions the quality of aggregate data. Due to the diverse approaches to data aggregation and measurement issues, the findings from the aggregate data are not always consistent with the findings from representative micro-data analyses. This may be a more acute problem in developing countries than in developed countries. For example, Young (2003), Holz (2014), Xiong (2018), and Chen et al. (2019) question the quality of aggregate data published by the Chinese government. Carter et al. (2002) measure agricultural productivity growth in China using three alternative data sets: one is a farm-level representative data set, and the other two are aggregate data sets at the provincial and national level, respectively. They found that using aggregate data sets might overestimate agricultural productivity growth in China for the period between 1988-1996.

At the micro level, improvement in aggregate productivity can be linked to the productivities of single production units (e.g., farms) by mechanically decomposing the former into three channels: (*i*) improvement in within-firm performance, (*ii*) improvement in between-firm resource reallocation among existing firms, and (*iii*) firm entry and exit (see Cusolito and Maloney, 2018; Fuglie et al., 2020). Over the past two decades, with the growing availability of micro-level data, the literature has observed a shift in analytical paradigm and measurement in understanding productivity and its determinants, i.e., a shift from using aggregate data to focusing on micro-level data. This shift is termed the "second wave" of productivity analysis in a recent World Bank report by Cusolito and Maloney (2018). So far, the achievement in this shift has been fruitful in the manufacturing sector (see reviews in Bartelsman and Doms, 2000; Tybout, 2000; Syverson, 2011; Restuccia and Rogerson, 2013; Hopenhyan, 2014). A general consensus from these analyses is that, even within narrowly defined industries, productive factors such as capital and labor are substantially misallocated across heterogeneous production units, i.e., more productive units are not using more resources, and such misallocation matters a lot for aggregate productivity.

In recent years, a similar analytical framework and measurement strategies have been actively extended to the agricultural sector to facilitate our understanding of differences in aggregate agricultural productivity as well as the standards of living across countries and time. The findings are mixed so far, with some studies documenting substantial factor misallocation in various developing countries (e.g., Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Chen et al., 2021) and others find little factor misallocation (e.g., Shenoy, 2017; Gollin and Udry, 2021). The causes of factor misallocation in agriculture are diverse, while most studies focus on identifying the effect of land property rights. As the literature is emerging, my main purpose in this review is to take a step back and examine what has been found in recent studies that link micro farm-level production data to aggregate agricultural productivity in various countries. This review does not intend to list all relevant studies, but rather aims at sorting out the main threads and findings so far.

2.1.1. STRUCTURE OF THIS REVIEW

Before I start to lay out the structure of this review, two things need to be made clear: First, as the title indicates, the starting point of this review is the agricultural sector at the micro level. This implies that I will exclude a vast number of important studies focusing on the non-agricultural sector.[2] Moreover, I will also exclude studies using aggregate data to understand agricultural productivity growth.[3] Instead, I review the studies that attempt to bridge micro-level variations with aggregate outcomes, where empirically the primary unit of analysis is often at the farm level. Nevertheless, discussions at the plot level or village level will also be included when necessary.

[2] For these, readers are recommended to refer to reviews in Bartelsman and Dom (2000), Tybout (2000), Syverson (2011), Hopenhyan (2014), as well as some general discussions in Restuccia and Rogerson (2013, 2017).
[3] For macro studies, readers are suggested to refer to for example McMillan et al. (1989), Lin (1992), Wen (1993), Huang and Rozelle (1996), Cao and Birchenall (2013), and Gong (2018).

Second, the productivity concept that is key to the analysis is *total factor productivity* (hereafter TFP); partial agricultural productivity measures such as labor productivity and/or land productivity are not the focus of this review, but they will be specified when necessary for intended discussions. Since measuring TFP either at the farm level or at the aggregate level is empirically challenging, I therefore will also devote some space to discuss the methodological and measurement issues related to micro-level TFP estimation and its aggregation.

From these starting points, I use the framework in Restuccia and Rogerson (2017) to organize this review into two broad parts. In particular, in Section 2.2, I review the literature that uses an *indirect approach* to study how important factor misallocation is in the agricultural sector, that is, what is the economic cost of misallocation. In Section 2.3, I then review the *direct approach* that attempts to identify the specific sources of factor misallocation in agriculture, i.e., the causes of factor misallocation. In Section 2.4, I briefly synthesize the discussions and provide reflections regarding what might be done in the future studies.

2.2. THE INDIRECT APPROACH: QUANTITATIVE IMPORTANCE OF MISALLOCATION

The main purpose of adopting the indirect approach is to understand *how important misallocation is* in accounting for the low aggregate agricultural productivity or living standards in some economies with a large agricultural sector. It is denoted as "indirect" because the approach often seeks to quantify the extent of misallocation without identifying the underlying source of the misallocation (Restuccia and Rogerson, 2017). In this section, I start with a simple quantitative framework that has been frequently adopted to quantify the magnitudes of factor misallocation in the agricultural sector. Then I review how the framework is usually combined with agricultural production data in several empirical studies to generate meaningful conclusions about factor misallocation. In the last part of this section, I discuss what these empirical findings imply for agricultural productivity policies and their advantages and limitations.

2.2.1. A QUANTITATIVE FRAMEWORK

The structural model that has been adopted most frequently to quantify to what extent productive factors are misallocated in the agricultural sector is perhaps the "span of control" model originating from Lucas (1978). Applications of this model to misallocation analysis are seen, for example, in Adamopoulos and Restuccia (2014), Restuccia and Santaeulàlia-Llopis (2017), Adamopoulos and Restuccia (2020), Adamopoulos et al. (2020), Ayerst et al. (2020), and Chen et al. (2021). In particular, the model features separable production and managerial technologies, where the production technology is often assumed to have constant returns to scale, while the managerial technology has two elements: variable managerial skills for heterogeneous farm operators and decreasing returns to scale. Instead of presenting a generic form of the model (see for example Restuccia and Rogerson, 2017), let us consider a more specific case where a rural economy containing I farms, and each farm $i = 1,2, \dots, I$ produces a homogeneous agricultural good by combining its managerial skill s_i with productive factor inputs including capital, labor, and land. In this case, the simplest yet very useful type of production function for farm i may take the following form,

$$y_i = s_i^{1-\gamma} \left(k_i^{\alpha} n_i^{\beta} l_i^{1-\alpha-\beta}\right)^{\gamma} \tag{2.1}$$

where y_i measures farm output; k_i measures capital input; n_i measures labor input and l_i measures land input; α and β are parameters of the Cobb-Douglas production technology, and $\gamma \in (0,1)$ is Lucas's "span of control" parameter. Together, $\alpha\gamma$ measures capital income share, $\beta\gamma$ measures labor income share, and $(1-\alpha-\beta)\gamma$ measures land income share in a growth accounting sense. Farm-level TFP is then obtained residually as

$$TFP_i \equiv s_i^{1-\gamma} = \frac{y_i}{\left(k_i^{\alpha} n_i^{\beta} l_i^{1-\alpha-\beta}\right)^{\gamma}} \tag{2.2}$$

To see what efficient resource allocation in a *static* equilibrium looks like, let us assume that a social planner of this rural economy intends to maximize total agricultural output by allocating its total resource endowments, i.e., total capital K, total labor N and total land L across the existing I farms, given the distribution of farms' managerial skills. Formally, this problem can be expressed as the maximization of aggregate agricultural production, which is a simple sum of all the outputs from individual farms [4]

$$\max Y = \sum_{i}^{I} y_i \tag{2.3}$$

subject to the farm-level production function in equation (2.1), and to the economy-wide resource endowments:

$$\sum_{i}^{I} k_i = K; \sum_{i}^{I} n_i = N; \sum_{i}^{I} l_i = L; \tag{2.4}$$

Before we move on to derive the optimal allocation schemes of the economy, two points might be noteworthy. First, it might be arguable that the behavioral assumption

[4] In other non-agricultural sectors, a proper aggregation with endogenous micro-level output price may be more suitable (see, for example, in Melitz, 2003 and Hsieh and Klenow, 2009 when markets are monopolistically competitive).

about the social planner, i.e., output maximization, is appropriate. For countries such as China and Vietnam that strongly emphasize food self-sufficiency, this assumption may be plausible. Second, the distribution of managerial skills or talents across the economy is usually unobservable to the social planner, and therefore achieving allocative efficiency through *planned* resource allocation and production will be difficult, and sometimes it may cause undesired consequences such as those that have been observed in the previously planned economies (see Rozelle and Swinnen, 2004, for a review).

Nevertheless, let us assume that these assumptions are satisfied so that we can derive the first-best allocation schemes. In particular, the first order conditions of solving this social planner's problem would give the unique scheme of efficient resource allocation across farms, where:

$$k_i^e = \frac{s_i}{\sum_i^I s_i} K;\ n_i^e = \frac{s_i}{\sum_i^I s_i} N;\ l_i^e = \frac{s_i}{\sum_i^I s_i} L; \tag{2.5}$$

where the superscript e denotes efficient resource allocation. Equations (2.1) - (2.5) immediately imply three possible approaches to quantify the importance of misallocation. First, equation (2.5) implies that, in a static efficient allocation of resources, farms with higher managerial skills s_i, i.e., higher farm-level TFP_i, should command more resources in production. That is, the farm-level use of each input should be strongly positively correlated with farm-level TFPs. To this end, a quick check of the correlation between observed input use and estimated farm-level productivities, e.g., by scatter plots or by correlation coefficient estimations, would provide some first evidence for discussing the severity of misallocation for each single factor.

Second, a more rigorous way to quantify the potential misallocation may be realized through two additional steps: (*i*) to derive the aggregate production function under efficient resource allocation according to equation (2.5), and use it to construct counterfactuals, that is, what would have been the aggregate output if resources were efficiently allocated across existing farms; and (*ii*) to evaluate the counterfactuals against the actual data collected to assess gains in aggregate output. To see how, let us put equation (2.5) back into the production aggregation in equation (2.3), then the aggregate output under efficient resource allocation will be:

$$\begin{aligned} Y^e &= \sum_j^I \left(s_j^{1-\gamma} \left[\left(\frac{s_j}{\sum_i^I s_i} K \right)^{\alpha} \left(\frac{s_j}{\sum_i^I s_i} N \right)^{\beta} \left(\frac{s_j}{\sum_i^I s_i} L \right)^{1-\alpha-\beta} \right]^{\gamma} \right) \\ &= \left(\sum_j^I s_j \right)^{1-\gamma} \left(K^{\alpha} N^{\beta} L^{1-\alpha-\beta} \right)^{\gamma} \end{aligned} \tag{2.6}$$

where the term $\left(\sum_j^I s_j\right)^{1-\gamma}$ can be thought of as aggregate TFP under efficient resource allocation, i.e., $TFP^e = \left(\sum_j^I s_j\right)^{1-\gamma}$. Then one uses data that has been collected to compute Y^e, and relative gain in aggregate output can be obtained by

$$Relative\ gain\ in\ aggregate\ output = \frac{Y^e - Y^a}{Y^a} \tag{2.7}$$

where Y^a is the actual aggregate output observed from the data. It is important to note that since total resources endowments are held fixed in both Y^e and Y^a, this output gain is exactly also the gain in aggregate agricultural productivity. One of the shortcomings of this aggregate production function approach is that it cannot separate the sources of misallocation, i.e., it is not known from which productive factor(s) the output or productivity gain should come from.

Third, one can also rely on the measured dispersions in the marginal product of capital, land, or labor to evaluate the extent of misallocation in each productive factor. This is a more fundamental approach, because essentially efficient resource allocation requires marginal products to be equated across farms. Dispersions of certain factors would imply the existence of misallocation of these factors. However, the problem with this approach is that the marginal products are not directly observable from the data. In empirics, one must make some structural assumptions to link the marginal products to observables. In the structural model presented here, the Cobb-Douglas production function allows us to link the marginal products to the average products, which are indeed observable. To see this, let us take the allocation of land as an example. The marginal product of land (MPL) for farm i is simply:

$$MPL_i = (1 - \alpha - \beta)\gamma \frac{y_i}{l_i} \propto \frac{y_i}{l_i} = APL_i \tag{2.8}$$

which is proportional to the average product of land (APL) for farm i. Therefore, equalization of MPL_i across farms also implies equalization of APL_i, and any detected dispersion in APL would therefore also indicate land misallocation.

Beyond the three possible approaches we just discussed, some studies also rely on estimating the *revenue-based* aggregate TFP measure (TFPR) and then contrast it to the *quantity-based* aggregate TFP measure (TFPQ) to evaluate the gains or losses in aggregate productivity (see, for example, Hsieh and Klenow, 2009; Adamopoulos et al., 2020; Ayerst et al., 2020). However, as Gollin and Udry (2021) pointed out, if farms produce highly homogeneous agricultural goods in a simple crop production pattern, then there is no need to distinguish between these two measures because farms have little market power in the output market, and one can therefore directly compare outputs of different farms without worrying too much about markups and pricing strategies. Nevertheless, I sketch this alternative approach in the Appendix. In the next section, I bring the quantitative measures of factor misallocation in this section to the data. I also discuss the empirical challenges and current findings in the literature.

2.2.2. BRINGING THE MODEL TO DATA

Although the indirect approach presented above is simple and straightforward, bringing it to the data is challenging. The framework indicates that constructing a set of accurate and comparable productivity *levels* across farms and then empirically measuring the dispersion of the productivity distribution should be put at the center of the indirect approach. This is because quantifying the importance of resource misallocation largely relies on those levels. To fulfill this requirement, farms are better drawn independently from an identical distribution such that the estimated dispersions are clear to interpret (see Bartelsman and Wolf, 2018). This is particularly important for studies using cross-sectional data. In many survey data sets involving agricultural households in developing countries, sample farms are usually drawn using a multistage cluster random sampling method, and therefore estimates of the standard errors need to be placed under clusters such as villages.

Moreover, the measured productivity levels, as defined in equation (2.2), should be considered as "physical" and are only related to farm operators' managerial skills as well as the physical quantities and qualities of agricultural inputs and outputs. Any confounding effects from input and output prices reflecting market powers or speculative opportunities may bias the TFP estimation (see discussions in Foster et al., 2008; Hsieh and Klenow, 2009). This does not mean that the price information is not needed from the potential data sets. Instead, because agricultural production among smallholders in many developing countries often involves using multiple inputs to produce multiple agricultural outputs in a production season, aggregating these multiple inputs and outputs to the farm level inevitably requires researchers to use prices to construct the relevant monetary values such that the aggregations are meaningful.[5]

Beyond these input and output data requirements, the indirect approach has an advantage over the direct approach that we are going to discuss in next section, namely, it has less restrictions on the time-dimension of the data. While the latter often requires longitudinal data or quasi-experimental data, the former can also work with cross-sectional data, though there may be greater challenges in addressing the potential confounding effects, for instance, from the unobserved time-invariant heterogeneities at the farm level. Since farm-level data is most often applied to study resource misallocation, in the

[5] For easier aggregation, the relevant literature so far mostly focuses only on the production of crops, which usually include staple crops and/or cash crops. The broader concept of agriculture such as livestock, grazing, forestry and fishing are often excluded. Including the production of these non-crop agricultural goods should be cautious as their production technologies can be very different. I do not expand the discussion here as it is only a side issue (but is still very important) for our discussions in this review. Readers who are interested in these issues may refer to FAO's guidelines for productivity measurement in agriculture (GSARS, 2018), as well as some early discussions for instance in Nazrul (2001) and OECD's productivity manual (OECD, 2001).

following, I therefore discuss the application of farm-level data as an empirical example. However, I also notice that some recent studies using plot-level data have made a significant contribution to the literature using the indirect approach. I leave the review of these to the next subsection.

As an example, suppose that we have a cross-sectional survey data set randomly collected from a population group of farming households. The data set should at least include the monetary values of input and output in agricultural production. In rural household surveys, most data sets, such as the World Bank's renowned Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) data sets collected from eight sub-Saharan African countries, would contain detailed information on the physical quantities of agricultural inputs and outputs. The biggest advantage of these data sets over plant-level manufacturing data sets is that the former often also collect input and output price information beyond the physical quantities. Output prices are usually the farm-gate prices obtained by farmers, while prices for intermediate inputs such as fertilizers, pesticides, and fuels are market prices of purchasing these inputs. Factor inputs, including capital, labor, and land, can also be valued by their rental rates or wages.

However, given my field experiences in many villages in China, some physical quantities and prices for intermediate inputs are extremely difficult to collect in practice. This is especially true for chemical fertilizers and pesticides because of the diverse brands, contents, and prices of the products. For these inputs, the alternative and perhaps more accurate information that can be collected in field work may be the total monetary costs by crops or by farms. However, there will be additional issues if monetary costs are collected: Do these costs truly reflect differences in input quantities and qualities? Or maybe they only reflect differences in prices due to market structures? This is a particularly acute problem if the studied region is large in geographic scale, under which situation the same product is likely to have different market prices across subregions. Nevertheless, the usual approach in the literature to deal with different prices over time and space is to use a set of common prices to evaluate all quantities such that the observed variation in monetary values reflect as much as possible the differences in physical quantities.

Output. Now assume that the available farm-level data set contains both quantity and prices information of inputs and outputs. To measure farm output, two approaches are often used: one uses farm-level gross output value (for example, in Ayerst et al., 2020), and the other uses farm-level value-added that subtracts intermediate input costs from the gross output value (e.g., in Adamopoulos et al., 2020; Restuccia and Santaeulàlia-Llopis, 2017; Chen et al., 2021). The right-hand side of equation (2.1) does not contain intermediate inputs; therefore, in our framework it uses value-added to measure farm-level output. However, it should be noted that because new technology is often embodied in improved intermediate inputs (e.g., using hybrid seeds and more effective agrochemicals), the use of value-added may understate the contribution of these intermediate inputs to agricultural productivity growth (Fuglie et al., 2020).

Input. Measures of labor and land input are relatively straightforward.[6] Most studies would also carefully control for land qualities such as elevation, slope, soil organic matter, rainfall, and temperature, and occasionally also control for labor qualities such as gender, age, education, and health conditions. But a minor issue regarding land input measures might be noteworthy. That is, the land input should be operational farm size instead of crop sown area. This matters because in some places a single piece of land might be used rotationally to produce multiple crops in a production season, such as the often-seen maize-wheat or wheat-soybean double-cropping in Asia and South America. The measure of capital is perhaps the most challenging part. So far, the literature has been somewhat disappointing on this issue, as I will discuss in more detail in Section 2.4. In summary, the first reason is that there are numerous types of capital on which an agricultural household can count, such as agricultural machinery, storage facilities, small tools, a transportation vehicle, etc. The second reason is that measuring the flow services cost provided by capital stocks can be challenging using the perennial inventory methods (PIM) as it requires to assume an appropriate capital depreciation rate (see more discussions in GSARS, 2018).

Elasticities. Suppose up to this end we have well-prepared the input and output data for equation (2.2). To obtain farm-level TFPs, we still need information on the parameters (output elasticities) of the production function, i.e., information of $\alpha\gamma$, $\beta\gamma$ and $(1-\alpha-\beta)\gamma$. Syverson (2011) summarizes several approaches that are commonly used to obtain these elasticities in the literature. Put simply, one approach is *computational* and based on cost-minimizing farms equating output elasticities with factor income shares under perfect competition and constant returns to scale assumptions, and factor income shares can be constructed directly from observed production data. Another approach is *econometric* in that output elasticities are estimated by estimating the production function. For example, one may simply take logarithms on both sides of equation (2.1) and use OLS to estimate the regression model $\ln y_i = \delta_0 + \delta_1 \ln k_i + \delta_2 \ln n_i + \delta_3 \ln l_i + \mu_i$, where the log TFP of farm i (i.e., $\ln s_i^{1-\gamma}$) is simply the estimated *sum* of the constant term $\widehat{\delta_0}$ and the residual $\widehat{\mu_i}$. However, it is important to note that this model specification can be endogenous since factor input intensities are likely to be correlated with the error term component, which is an additive part of the measured productivity. In general, the computational approach is easier to implement in practice though it requires some additional assumptions

[6] Note that sometimes in the literature both output and inputs are often normalized by labor input, i.e., measured in terms of per unit labor input (such as hours, days or labor heads, see for example in Adamopoulos et al., 2020 and Chen et al., 2021). The advantage of such a manipulation of data is to make the model more tractable and less subject to computational cumbersomeness. The disadvantage of this manipulation is that it implicitly assumes that there is no labor misallocation across existing farms within the agricultural sector. However, as Chen et al. (2021) pointed out, this assumption might be plausible given that most farms only use family labor (not hired labor) for production in many less developed countries with smallholder production, and family labor surely cannot be easily and effectively reallocated across households along with the reallocation of land and capital. Therefore, such an assumption usually would not significantly affect the unbiasedness of misallocation estimation within the agricultural sector. Nevertheless, labor allocation still can be severely distorted across sectors, e.g., the *Hukou* system in China that distorts rural-urban labor mobility (see Ngai et al., 2019).

that may not be realistic for certain studies such as those involving manufacturing firms.[7] But for agricultural production, the focus of this review, the computational approach seems to be suitable given those required assumptions. It is important to note that factors' output elasticities obtained by either approach are often assumed to be constant across farms in the literature. This assumption, however, may still be debatable, as the output elasticities were empirically found to be very different across regions (Gong, 2018) and across crops (Wang et al., 2016).

Using the information of measured output, inputs, and output elasticities, it is then possible to estimate the TFP for each farm in the sample and to construct dispersion measures (e.g., using standard deviations or interquartile ranges) and evaluate the importance of factor misallocation following the approaches discussed in Section 2.1. In the following, I review the important findings so far in the literature based on this or on variants of this indirect approach.

2.2.3. FINDINGS IN THE LITERATURE USING THE INDIRECT APPROACH

Using the indirect approach, most studies in the literature have documented that there is a quantitatively substantial amount of misallocation of productive factors across farms in many developing countries. Such a misallocation can explain a large part of the low aggregate agricultural productivity and hence the low standards of living in those countries. Restuccia and Rogerson (2017) have reviewed four such studies, including Adamopoulos and Restuccia (2014), Restuccia and Santaeulàlia-Llopis (2017), Adamopoulos et al. (2020) and Chen et al. (2021). I only briefly summarize the first three studies here and leave the last one for later sections, as it is not completely indirect.

In particular, Adamopoulos and Restuccia (2014) document a long list of "pro-small" distortive farm size policies in many developing countries, e.g., in the forms of land holding ceiling, land tax, input subsidy, and production quotas. Their main finding is that misallocation caused by these farm size distortions can explain a large proportion of the differences in aggregate productivity and farm sizes between the rich and poor countries. Restuccia and Santaeulàlia-Llopis (2017) exploit a nationally representative farm-level data set collected in Malawi in 2010/11 under the LSMS-ISA survey. They estimate a cross-sectional distribution of farm-level TFPs and find that there is a huge dispersion in the distribution; meanwhile, factor inputs such as land and capital are relatively equally distributed across these sampled farms. Given the indirect approach, they estimate that static gains in aggregate agricultural output or productivity for the entire country of Malawi would increase by 360% if land and capital were efficiently allocated according to their

[7] Readers who are interested in the econometric estimation of production functions that facing severe endogeneity issues are referred to the seminal studies of Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), Ackerberg et al. (2015), and Gandhi et al. (2020).

farm-specific productivities. Adamopoulos et al. (2020) study a panel data set between 1993-2002 in China, collected under the National Fixed Point (NFP) surveys. They document that the allocations of land and capital across farms during that period are generally irrelevant to the distribution of farm-level TFPs, and this misallocation of resources has led to an overall annual average loss of 53% in aggregate agricultural output and productivity.

Beyond these studies, several recent papers have also explored the importance of factor misallocation in aggregate agricultural productivity using the indirect approach. For example, Ayerst et al. (2020) study the development of the agricultural sector in Vietnam for the period between 2006 and 2016. Using a biennial household panel data set consisting of 2,087 households, they find that crop output grows with 4% on average per year over this balanced panel of households. However, this growth is mainly due to productivity improvements from increased use of intermediate inputs such as fertilizer, while factor misallocation is still high and likely to increase during this period despite the improving aggregate agricultural productivity. In particular, relying on the indirect approach to quantify the importance of factor misallocation, they document that the static gain in aggregate productivity is up to 68% for the period between 2006 and 2010, and even larger at 80% for the period between 2012 and 2016, clearly indicating a worsened misallocation over time in Vietnam. Moreover, as a step forward, they also estimate the productivity gains, respectively, for the north and south regions and find that the misallocation is significantly larger in the north than in the south: it was two times larger between 2006-2010 and approximately four times larger between 2012-2016. It seems that the worsened misallocation over time for the whole country all comes from the northern region, which increased by 76 percentage points between these two periods, while in the southern region it increased only by 4 percentage points. In a brief exploration of why the northern region has performed worse in allocative efficiency, they argue that institutional constraints such as land allocation, access to water for irrigation, and restrictions on crop choice have played an important role.

2.2.4. ARE THE FACTORS SO MISALLOCATED?

The general finding from the indirect approach is that the productive factors are severely misallocated between farms in many developing countries. However, these findings are not without limitations. Research works from, for example, Syverson (2011), Restuccia and Rogerson (2017), Bartelsman and Wolf (2018), Cusolito and Maloney (2018), and Fuglie et al. (2020) have carefully discussed the potential overestimation of factor misallocation both in the agricultural sector and in the manufacturing sector. The general argument is that misallocation has been overestimated due to mismeasurements of the dispersion in farm-level TFPs. The relevant question that has been asked is: can these detected dispersions in TFPs be fully attributed to factor misallocation? The short answer seems to be "no."

For example, Restuccia and Rogerson (2017) summarize three alternative explanations for observed dispersions in TFPs, including production function heterogeneities, adjustment cost, and measurement errors. Bartelsman and Wolf (2018) put them as statistical issues and economic issues, where the latter adapts the framework in Syverson (2011).[8] Cusolito and Maloney (2018) expand the reasons to also include output qualities and risk and uncertainty.

Specifically for the agricultural sector, measurement errors in input and output data can be a particularly acute problem. Adjustment costs for land transactions can also be a problem if they are farm-size-dependent (see Chen et al., 2021). To address these challenges, recent studies of factor misallocation in the agricultural sector attempt to utilize the rich data available to isolate potential confounding effects of these factors. A recent study of Gollin and Udry (2021) attempts to address the challenge by distinguishing misallocation from other potential sources that cause productivity dispersions. They exploit plot-level panel data from LSMS-ISA surveys conducted in Tanzania and Uganda, where farmers produce quite homogeneous agricultural outputs. They argue that this type of data allows them to quantify factor misallocation more precisely, because observed within-season variation in input use intensity and output across plots cannot be interpreted as misallocation, since farmers should have faced no market imperfection in allocating resources across their own plots. Using the data and facilitated by a theoretical framework that models production processes as farmers sequentially (and endogenously) selecting plots, allocating inputs to individual plots, and realizing output, they particularly disentangle misallocation from three other sources of measured productivity dispersion at the farm level, i.e., idiosyncratic productivity shocks (e.g., weather and pests), measurement error, and unobserved heterogeneities in land quality. They find that these sources account for as much as 70% of variance in measured productivity; ignoring them could lead to an overstatement of productivity gains by a factor of two or three, and therefore also the potential importance of misallocation in explaining low aggregate productivity drops substantially.

Shenoy (2017) attempts to measure and separate misallocation caused by failures in the factor market and financial market in Thai villages. A key assumption made by the study is that all inputs can be instantly transferred between farmers within a village, and without cost. The perfect factor market allows farmers to achieve a perfect mix of various types of input before producing any output, but the credit market can be distorted toward certain input, for example, a loan for land may be easier to obtain than a loan for hired labor since the former can be used as collateral. Therefore, frictionless factor market only ensures perfect input mix but holds farm scale constant (e.g., the equalization of land-labor ratio across farms but with one credit-constrained factor fixed); frictionless financial

[8] In Syverson (2011), the economic issues may be summarized as the "within" firm factors such as managerial talents, higher-quality inputs, information technology and R&D, etc., and the "between" firm factors such as market competition, policy regulation and deregulation, flexible input markets, etc.

market will then facilitate to adjust the scale to its optimal level as well. Using the Townsend Thai Annual Household Survey data, he estimates rather small within-village misallocations among Thai rice farmers, which are 19% in 1996 and only 5% in 2008. These numbers are much smaller than the literature has usually documented. More importantly, he also finds that misallocation caused by factor market failures contributes little to improved agricultural productivity in Thailand between 1996 and 2008. Instead, the improvement in the credit market accounts for a large part of the reduced total misallocation. However, these studies that have attempted to correct for potential overestimation in factor misallocation are not free of criticism. For example, in a recent comment, Aragon et al. (2021) argue that Gollin and Udry (2021) have concluded incorrectly based on their own empirical evidence. Instead of downplaying the quantitative importance of misallocation in Tanzania and Uganda, they think that Gollin and Udry's findings actually corroborate the importance of misallocation that has been emphasized throughout the literature of macro-development economics. They also argue that using plot-level data would magnify the measure of productivity dispersion and hence overstate the importance of mismeasurement in understanding productivity difference, and therefore farm-level data is more reliable in similar analysis.

2.3. THE DIRECT APPROACH: UNDERLYING SOURCES OF MISALLOCATION

While the indirect approach still faces various challenges, a more appealing and policy-relevant approach is to directly isolate and test the impact of certain policies on factor misallocation. A great advantage of the direct approach is that it can circumvent the imposition of structural models that are considered necessary to quantify the extent of factor misallocation. As we have discussed in the end of Section 2.1, the indirect approach and direct approach have different purposes: the former answers how important is the misallocation, while the latter answers what causes the misallocation. Intuitively, we first need to understand the importance of factor misallocation in an economy, and then make efforts to understand what factors cause it for policy designs. The direct approach is more policy-relevant. Restuccia and Rogerson (2017) express their disappointment toward the existing manufacturing literature in applying the indirect approach, while noting that some factors have been identified that can account for large effects of misallocation in agriculture. The most studied and relevant cause of factor misallocation in the agricultural sector is perhaps land property rights. In the following, I review a few recent studies that investigate this specific source of factor misallocation.

In the first set of studies, the researchers attempt to identify the specific sources, but they may not be purely direct in methodology because they still build on hypothetical policy counterfactuals, i.e., what the productivity gains would have been if the studied policies or regulations were completely removed. For example, Chen et al. (2021) explore the factor misallocation in Ethiopia using two waves of LSMS-ISA survey data that were collected, respectively, in 2013/14 and 2015/16. They particularly focus on the impact of land rental market at zone level. They find that the effect of a counterfactual reallocation from no rentals to efficient rentals would increase zone-level agricultural productivity by 43% on average. Similarly, Bolhuis et al. (2020) exploit the substantial variation in land rental markets across states in India. They combine a quantitative model and micro-panel data to estimate land market distortions in each state and find that land rental activities have significant positive effect on agricultural productivity. They first set up the policy counterfactual as if farms operate only on their own lands instead of also on rented lands and estimate that the productivity would decline by 22% on average across states. On the other hand, they also find that if lands were reallocated efficiently in each state, productivity would increase by 29% on average. Alternatively, Le (2020) questions the role of crop choice restrictions on aggregate productivity in Vietnam, a potential cause of factor misallocation that is also briefly discussed by Ayerst et al. (2020). He finds that the Rice Land Designation Policy (RLDP) in Vietnam, a centralized land-use planning system that forces farmers to produce rice on almost 45% of their land plots, causes land and labor misallocation in agriculture and non-trivially decreases aggregate agricultural productivity. He shows that if crop choice restrictions from RLDP were completely removed in a hypothetical counterfactual setting, the real GDP per capita would increase by approximately 8%, and agricultural TFP would rise by 38%, along with a reduction in agricultural employment and an increase in average farm size. A common feature of these studies is that each of them has successfully identified land market distortions as a source of factor misallocation, although the counterfactuals they build to evaluate the extent of factor misallocation are hypothetical.

Different from the above studies are those that directly study the impact of land policies on factor misallocation and productivity gains based on some natural experiments and using before-and-after reform panel data sets. In particular, the paper of de Janvry et al. (2015) studies the impact of a land certification program in Mexico in the 1990s. Although they do not directly measure misallocation and agricultural productivity, they do find that removing the link between land use and land rights through the issuance of ownership certificates results in substantial land and labor reallocations. The reallocation of labor across agricultural and non-agricultural sectors is particularly substantial: households obtaining land certificates are subsequently 28% more likely to have a migrant member in the household. Adamopoulos and Restuccia (2020) focus on the impact of the 1988 land reform in the Philippines that imposed a ceiling on land holdings, redistributed above-ceiling lands to landless and smallholder households, and restricted land transfers of the redistributed farmlands. Using a quantitative model and micro-level panel data on sample farms covering the periods before and after the reform, they find that the land reform has reduced average farm size by 34% and agricultural labor productivity by 17%.

Two recent studies focusing on China, respectively, from Chari et al. (2020) and Zhao (2020) are particularly interesting to review, as both of them exploit the same natural experiment – a legislative land reform in China – to identify the source of factor misallocation, while their findings somehow contradict each other. Before I start to review their studies, it might be helpful to have a quick look at the natural experiment they study. In particular, in August 2002, the Chinese government passed the Rural Land Contracting Law (RLCL), which came into effect from March 2003. On the one hand, the law legalized farmers' rights to lease their land while reiterating existing protections for the security of land rights, and in this way it aims to improve land tenure rights by encouraging and protecting *voluntary* land transfers among households. On the other hand, the law also prohibited village-officials-led labor-contingent land reallocation within villages, i.e., administrative land adjustments to accommodate within-village demographic changes due to population growth or rural-urban migration. In this respect, the law still aims to enhance land tenure rights, but alternatively by restraining *involuntary* land reallocations among households. The studies by Chari et al. (2020) and Zhao (2020) are motivated by precisely these two legislative features.

Specifically, Chari et al. (2020) attempt to answer a critical policy-relevant question that to what extent the within-sector misallocation of land and between-sector misallocation of labor can be rectified by reducing transaction costs in agricultural land market. They exploited the NFP survey panel data set between the period 2003-2010 and use its information to construct key outcome variables including household-level land rental activities (land rent-in and rent-out), labor use and migration, and aggregate agricultural output and productivity, etc. To identify the impact of the RLCL in various difference-in-difference estimations, the paper relies heavily on the exogenous variation of the *provincial level implementation time* of the RLCL across China.[9] They also controlled for the potential confounding effect from a major agricultural tax reform during their study period. They find that after the reform (was implemented in different provinces), the amount of land area rented in at the household level increased by more than 7%, as did the land area rented out;[10] aggregate output, measured by village-level real agricultural revenue, increased by 8%; and aggregate productivity, measured by the village-level agricultural revenue per unit of land (i.e., aggregate land productivity), increased by 10%.

Alternatively, Zhao (2020) makes a distinction by studying the impact of prohibiting village-level administrative land reallocation in the RLCL. Similarly to the paper by Chari et al. (2020), she also uses the NFP panel data, but by focusing on the period between 1986 and 2008. To identify the impact of this law reform on a set of village-level economic

[9] To support this argument, the authors panel regress the province-level implementation timing on a set of provincial agricultural outcomes, e.g., per capita rural income level, number of agricultural employments, per capita rural expenditures on food, clothing and housing, number of land disputes news articles, share of households experienced land reallocation, etc. They find that these agricultural outcomes are not directly deriving the decision of the provincial government regarding the reform.

[10] Though the authors use inverse hyperbolic sine function to transform some of the dependent variables, their estimated parameters are still directly interpreted as percentage changes like a logarithmic transformation.

outcomes such as off-farm labor ratio, cross-household income inequality, average land productivity, and average per capita net income, Zhao (2020) does not explore the variation in the law implementation across provinces. Instead, the law is treated as a binary time indicator in the paper and equals one for pre-reform periods and zero for post-reform periods. This time indicator is then interacted with the pre-reform annual probability of administrative land reallocations and/or the pre-reform land transfer ratio; both were estimated from the NFP household panel data. Therefore, the impact of the law reform is captured by interpreting the parameter estimates (from difference-in-difference panel regressions) as measures that capture the impact of a village's pre-reform land tenure security on the pre-reform village-level outcomes, relative to its post-reform outcomes. The key findings of the paper are that the law reform, which stopped village-level administrative land reallocations, increased village-level off-farm labor and average per capita net income by 7% and 6.5%, respectively; however, it also finds that elimination of administrative land reallocations following the law reduced total agricultural output by 6% and also increased significantly the intra-village income inequality.

These two articles certainly have made significant methodological contributions to our understanding of the specific causes of factor misallocation in the agricultural sector of China. However, in terms of policy implications, their findings are somewhat frustrating. In particular, recall that both papers study the impact of the RLCL using the same data source (though with different subsamples in time and space), but if we put them together, it is not so difficult to notice that their findings strongly contradict each other: Chari et al. (2020) find that the implementation of RLCL *increased* agricultural output and productivity by 8% and 10% respectively, while Zhao (2020) finds that RLCL *decreased* agricultural output by approximately 6%.[11] Although their studies were motivated by the different aspects of legal reform, that is, Chari et al. (2020) focused on increased voluntary land transfers due to the law and Zhao (2020) alternatively focused on the prohibition of involuntary labor-contingent land transfers, their estimations cannot isolate the impacts of the law from these different terms of regulations. This is to say, their studies unambiguously examine the *overall impact* of the RLCL, rather than a single aspect of it. It remains unclear why these two studies have come to contradictory conclusions. Since output information is observable in the NFP data set, there should be concrete evidence about whether output has increased or decreased, before and after the implementation of RLCL. In this regard, future studies are needed, for example, using the same subsamples from the NFP data set but with different identification strategies, to understand the true impact of RLCL on factor misallocation and aggregate agricultural productivity in China.

[11] Since Zhao (2020) measures agricultural output as the average agricultural output per unit land, the more comparable measure in the Chari et al. (2020) paper is aggregate agricultural productivity, defined as village-level aggregate revenue per unit land. In this respect, it seems that different output or productivity measures are not the cause of these contradictory findings.

2.4. SUMMARY AND FUTURE DIRECTIONS

In this review, I briefly survey what is known so far for factor misallocation in the agricultural sector in different countries. Put simply, most studies have found that factor misallocation has quantitatively non-trivial consequences on aggregate agricultural output level and productivity. The approach applied to document these findings is mostly indirect, as discussed in Section 2.2. Using the direct approach, as in Section 2.3, the literature that studies the agricultural sector has identified weak land institutions and underdeveloped land markets as major sources of factor misallocation in many developing countries. In general, we can see that although the total number of relevant studies with either approach is still small, the literature is surely emerging and growing very fast in recent years. As the literature continues to advance, in the following, I briefly lay out a few important questions that I think the future research agenda might be interested in addressing.

2.4.1. INTERMEDIATE INPUT QUALITY AND MISALLOCATION

A less studied but surely important aspect that is almost missing in all data sets is the quality measure of agricultural inputs. So far, the best captured quality information in the literature is about land; most studies control for several dimensions of agricultural land quality in their estimation of farm-level TFPs (see for example Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020). However, measures of labor quality distinguished by, for instance, gender, age, education, and farming experience are usually ignored. An exception is Chen et al. (2021) who use quality-adjusted effective labor input to estimate farm-level productivities in Ethiopia.

The most severe data quality problem of inputs perhaps comes from the measure of intermediate inputs. Although many studies have documented that quality improvements in seeds, chemical fertilizers, and agrochemicals contributed significantly to productivity improvement throughout history, such improvements have not been well reflected in factor misallocation analyses. The problem is particularly acute when longer-term panel data is applied. For example, a certain amount of chemical fertilizer applied ten years ago could be much less effective in crop production than the same quantity of fertilizer applied today. Even if this is measured in terms of nutrient components, improved application methods will affect the output level, and thus also the productivity estimates.

What may complicate the situation is the fact that intermediate inputs in the market today are often very diversified even in some less developed countries. The market contains various kinds of products and therefore allows farmers to voluntarily choose among many that are (however significantly or insignificantly) different in their qualities. In a geographically concentrated study area, the quality differences may be reflected in the observed market prices of inputs, and taking these price variations into consideration, instead of using a set of common prices across both time and space, may capture these quality heterogeneities to a certain degree. However, if the intended study is conducted in a larger area, prices variations may also reflect market imperfections such as market power and transportation costs and therefore cannot accurately reflect quality heterogeneities. Although it seems that there is a great need to include more quality information in the farm-level productivity estimation, the task of collecting this information, however, can be quite challenging in practice. Given my own field survey experience in rural China, intermediate input quality information usually is difficult to collect by asking farmers to recall the detailed characteristics or nutrient components of the products they have used.

Beyond measurement issues, little evidence has been documented for the potential misallocation of intermediate inputs. For example, in Section 2.2, when we use value-added to measure farm-level output, an implicit assumption that is particularly related to misallocation analysis is that one cannot separate idiosyncratic farm-level distortions in intermediate inputs from those in agricultural output. This assumption might be plausible for studies in China where chemical fertilizers (and pesticides) are considered to be systematically overused (see, for example, Zhang et al., 2013; Cui et al., 2018). However, it might be a problem for other regions, such as sub-Saharan countries that are documented to have both fertilizer overuse and underuse issues (see for example Duflo et al., 2008; Schilbach, 2015). The questions are what might have caused this seemingly inefficient allocation of chemical fertilizers and whether such a distribution pattern of fertilizer use across farms can be considered as a misallocation. As the literature has been answering these questions extensively from microeconomic perspectives, we may need more theoretical explanations and empirical evidence from macroeconomic analysis.

2.4.2. CAPITAL QUALITY AND MISALLOCATION

Several studies have explicitly pointed out that capital input is severely misallocated in agricultural production in many developing countries. The reason for this is usually related to weak land institutions under a smallholder production system, in which farmers find it difficult to collateralize their land holdings for capital investment (see for example Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020). A question that might be asked following these findings is whether capital is really so misallocated across agricultural production units. Two reasons may justify asking this. First, the measure of capital input in agricultural production per se is very challenging. For example, using perpetual inventory method to evaluate capital stocks is notoriously difficult, as researchers must assume proper capital depreciation rates based on further assumptions on machinery types, use frequencies, capital wear-out speed, etc. Generating flow costs of capital services is also difficult given that the capital rental market is severely underdeveloped in many developing countries and obtaining the prices of capital often involves a huge amount of data imputations. The quality of capital input may also matter. For example, Caunedo and Keller (2020) explore this issue carefully by constructing a novel data set that contains detailed tractor price information across sixteen countries between 2007 and 2017. They measure the stocks of quality-adjusted capital in agriculture in each country and find that the importance of capital in accounting for cross-country differences in agricultural labor productivity is almost doubled if the differences in capital quality are accounted for. To sum up, ignorance of these and other similar facts may lead to sizable measurement errors in capital input, and hence bias productivity estimation as well as misallocation assessment.

Second, across the world, mechanization and automation in agricultural production have been growing quickly along with the fast development of small agricultural machinery, machinery services market, and agricultural digitalization. Given this background, an ignored phenomenon - mechanization outsourcing or hired machinery services for smallholders - that is particularly trending in rural China in recent years may as well have important implications for quantifying capital misallocation in its agricultural sector (see for example Yang et al., 2013; Wang et al., 2016; Zhang et al., 2017). In particular, the popularity of mechanization outsourcing has enabled smallholders in China who are initially credit-constrained in agricultural machinery investment to alternatively hire machinery services with reasonable prices from other machinery owners such as local large-scale farm operators, cooperatives, and non-local professional machinery service providers. In this respect, input of agricultural land (including own land contracted from village collectives and land rented from other farmers under China's Household Responsibility System) is less likely constrained by insufficient capital input, and capital input can also be instantaneously adjusted to the desired level given land input. Therefore, mechanization outsourcing may not only directly reduce capital misallocation but may also facilitate land transfers without involving too much complementary capital input. However, detailed theoretical mechanisms about how this influences factor misallocation and empirically to what extent this affects the quantitative assessment of overall misallocation still need further studies. Although the trend of mechanization outsourcing has been less observed in other developing countries, China seems to be taking this advantage to cope with or adapt to some of its socioeconomical and sociopolitical institutions that are difficult to change in the short run. Understanding the impact of mechanization outsourcing therefore may also have important implications for other countries whose agricultural sector also features smallholders and faces some institutional barriers in the land market.

2.4.3. Farm entry and exit and labor reallocation across sectors

As we have discussed in Section 2.1, farm entry and exit can be considered as a special case of resource reallocation where the resources of exiting farms are fully reallocated to other incumbent farms or newly entered farms (Restuccia and Rogerson, 2017). It is important to note that the static equilibrium analysis in Section 2.2 cannot capture this dynamic effect since resources are allocated proportionally to farm-level productivities in the equilibrium, and the distributions of resources across farms are non-degenerating. What do farm entry and exit imply for resource reallocation and aggregate agricultural productivity growth? Understanding this dynamic inevitably involves using panel data sets that contain information on exit farms and entry farms over time. Intuitively, if exit farms have lower productivities than entry farms in the farm productivity distribution, then aggregate productivity is improved by mobility. However, this dynamic process of farm entry and exit (farm selection) can be endogenous and may also be distorted by public policies such that less productive farms stay while more productive farms exit (see for example Hopenhayn, 1992; Hopenhayn and Rogerson, 1993, Olley and Pakes, 1996; Melitz, 2003; Melitz and Polanec, 2015). In this way, aggregate productivity will be lower.

In the current literature, although the evidence from the manufacturing sector has been huge, the impacts of entry and exit of agricultural entities on agricultural productivity have been less studied. Two recent studies on China may shed some light. Specifically, Chari et al. (2020) and Wang et al. (2020) estimate the impact of farm entry and exit using the NFP survey data; they find, however, that this impact is less important for aggregate agricultural productivity improvement, both in absolute terms and compared to findings in the manufacturing sector. Note that, observations defined in the NFP survey are family farms, mostly smallholders. Therefore, the impact of production units such as agribusiness firms or farm cooperatives, which may play important roles in agricultural production in some specific regions, is not captured. No matter whether this is true or not, the number of studies available is still very limited, and more evidence is still needed in future research. Furthermore, even if it is true that farm entry and exit contribute little to aggregate agricultural productivity growth, we still cannot downplay the importance of farm entry and exit, as it can have a significant impact on cross-sectoral labor reallocation, which is the central theme in the study of agricultural productivity gap and structural transformation (see for example Lagakos and Waugh, 2013; Gollin et al. 2014; Ngai et al., 2019)

2.4.4. ALTERNATIVE WELFARE IMPLICATIONS OF FACTOR MISALLOCATION

So far, the impact of factor misallocation has been mainly linked to productivity growth. This might be justified by the stylized fact that cross-country differences in income or living standards can largely be explained by differences in cross-country productivities (see for example Caselli, 2005). However, while land misallocation (such as egalitarian land allocation in China, Vietnam, and several other developing countries) may reduce aggregate agricultural output level and productivity, it is also found to be associated with decreased within-village income inequality (see Zhao, 2020). This points back to the old debate between efficiency and equality and to welfare concepts that account for inequality aversion. More empirical evidence of this kind is surely needed for policy makers to design inclusive development strategies.

2.4.5. Evidence from alternative data sources

Finally, the data sets used to quantify misallocation and identify sources of misallocation are still limited to a few nationally representative data sets. For example, most studies in African countries rely on the LSMS-ISA data sets of the World Bank. In China, all findings on factor misallocation in agricultural sectors are based on the data set of the NFP survey panel data set.[12] This also includes several studies conducted by Chinese researchers and published in top peer-reviewed Chinese journals that are less familiar to non-Chinese-speaking international researchers (see for example Zhu et al., 2011; Gai et al., 2017; Gai et al., 2020; Wang et al., 2020). Empirical evidence from the use of alternative data sets is still needed to ensure that the documented misallocation is quantitatively significant and consistent across regions and data sets.

[12] A very recent exception is Gao et al. (2021), who use the household panel from Chinese Family Database.

APPENDIX

Following the quantitative framework in Section 2.1, in certain situations one may want to make additional behavioral assumptions on individual farm operators.[13] For example, we can alternatively assume that farming households choose capital, labor, and land to maximize farm profit given farm-specific distortions to output (τ_i^y), capital (τ_i^k), labor (τ_i^n), and land (τ_i^l). These distortions are quite generic such that they can be negative or positive depending on whether they represent a tax or a subsidy (Restuccia and Rogerson, 2008). The caveat part of these distortions is that they are idiosyncratic to specific farms. The prices of factor inputs, including capital rental rate R, wage rate w, and land rental rate r, are assumed to be exogenously determined in a perfectly competitive economy. The price of output is also exogenously determined and normalized to 1, and hence output y_i measures the real output of farm i.[14] Formally, this is expressed as

$$\max_{\{k_i, n_i, l_i\}} (1-\tau_i^y)y_i - (1+\tau_i^k)Rk_i - (1+\tau_i^n)wn_i - (1+\tau_i^l)rl_i \qquad (A2.1)$$

subject to the farm-level production technology $y_i = s_i^{1-\gamma}\left(k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}\right)^\gamma$. The first order conditions of this profit maximization problem with respect to capital, labor, and land are, respectively,

$$MRPK_i \triangleq \underbrace{s_i^{1-\gamma}\gamma\left(k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}\right)^{\gamma-1}\alpha\left(k_i^{\alpha-1} n_i^\beta l_i^{1-\alpha-\beta}\right) = \alpha\gamma\frac{y_i}{k_i}}_{this\ is\ the\ defined\ MRPK_i} = \underbrace{\frac{1+\tau_i^k}{1-\tau_i^y}R}_{MC_i} \qquad (A2.2)$$

$$MRPN_i \triangleq \underbrace{s_i^{1-\gamma}\gamma\left(k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}\right)^{\gamma-1}\beta\left(k_i^{\alpha} n_i^{\beta-1} l_i^{1-\alpha-\beta}\right) = \beta\gamma\frac{y_i}{n_i}}_{this\ is\ the\ defined\ MRPN_i} = \underbrace{\frac{1+\tau_i^n}{1-\tau_i^y}w}_{MC_i} \qquad (A2.3)$$

$$MRPL_i \triangleq \underbrace{s_i^{1-\gamma}\gamma\left(k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}\right)^{\gamma-1}(1-\alpha-\beta)\left(k_i^{\alpha} n_i^{\beta} l_i^{-\alpha-\beta}\right) = (1-\alpha-\beta)\gamma\frac{y_i}{l_i}}_{this\ is\ the\ defined\ MRPL_i}$$
$$= \underbrace{\frac{1+\tau_i^l}{1-\tau_i^y}r}_{MC_i} \qquad (A2.4)$$

where $MRPK_i$, $MRPN_i$, and $MRPL_i$ define the marginal *revenue* product of capital, labor, and land, respectively, and MC_i defines marginal cost. Clearly, marginal revenue products would not be equalized across farms if there are farm-specific idiosyncratic distortions in output and/or input markets, so aren't the average products y_i/k_i, y_i/n_i, and y_i/l_i. In

13 This behavioural assumption about farms is needed in some cases, while it can also be problematic.

14 Assuming that input and output prices are all exogenously determined in the agricultural sector is quite plausible for a system of smallholder production in many developing countries. In manufacturing sector, however, output prices are often endogenous because firms in the industry are often monopolistically competitive (see for example Hsieh and Klenow, 2009).

particular, they vary *proportionally* to these idiosyncratic distortions faced by each factor input ($1+\tau_i^k$, $1+\tau_i^n$ and $1+\tau_i^l$) relative to the output distortion ($1-\tau_i^y$). If there were no such distortions in factor inputs and output, then their marginal revenue products (and average products) should be equalized according to the marginal costs (i.e., factor prices) of production across households.

With information of prices, inputs, and output, these first order conditions allow us to identify either three of the four distortions since we have three equations for four unknown sources (τ_i^y, τ_i^k, τ_i^n, and τ_i^l). We cannot identify all of them at the same time (see discussions in Adamopoulos et al., 2020). But if we are confident that one of the distortions, e.g., the output distortion $\tau_i^y = 0$, is negligible for all farms in reality, then in this analytical framework we will be able to exactly identify all other distortions up to a scalar of the average production: $R/(\alpha\gamma)$ for capital, $w/(\beta\gamma)$ for labor, and $r/((1-\alpha-\beta)\gamma)$ for land.

Using these scalars, we can then also define a *summary measure of distortions* for each farm*:*

$$TFPR_i \triangleq \frac{y_i}{k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}} = \frac{y_i^\alpha y_i^\beta y_i^{1-\alpha-\beta}}{k_i^\alpha n_i^\beta l_i^{1-\alpha-\beta}} = \left(\frac{MRPK_i}{\alpha\gamma}\right)^\alpha \left(\frac{MRPK_i}{\beta\gamma}\right)^\beta \left(\frac{MRPK_i}{(1-\alpha-\beta)\gamma}\right)^{1-\alpha-\beta}$$

$$= \left(\frac{R}{\alpha\gamma}\right)^\alpha \left(\frac{w}{\beta\gamma}\right)^\beta \left(\frac{r}{(1-\alpha-\beta)\gamma}\right)^{1-\alpha-\beta} \frac{\left(1+\tau_i^k\right)^\alpha (1+\tau_i^n)^\beta \left(1+\tau_i^l\right)^{1-\alpha-\beta}}{1-\tau_i^y}$$

$$\Rightarrow TFPR_i \propto (MRPK_i)^\alpha (MRPN_i)^\beta (MRPL_i)^{1-\alpha-\beta}$$
$$\propto \frac{\left(1+\tau_i^k\right)^\alpha (1+\tau_i^n)^\beta \left(1+\tau_i^l\right)^{1-\alpha-\beta}}{1-\tau_i^y} \qquad (A2.5)$$

Note, this is only a measure of distortion that is constructed on purpose. It is constructed like this because we want this measure (*i*) to be closely related to the marginal revenue products of factors, and (*ii*) to capture all the distortions presented in the model. There is no need to think too much about the fact that this measure is related to output price and productivity. In fact, it is analogous to the "revenue productivity" as defined by Foster et al. (2008) and Hsieh and Klenow (2009), in terms of both measures being proportional to a summary distortion. In particular, the $TFPR_i$ is proportional to a *geometric average* of the marginal revenue product of factors, which is then also proportional to a geometric average of the distortions in each factor.

The ultimate purpose that we define $TFPR_i$ like this is to derive the aggregate TFP *with market distortions* and then compare this distorted aggregate TFP with the one derived from a social planner's problem (see Section 2.1). To see this, using the first order conditions, we are able to solve for the optimal factor demand for capital k_i^*, labor n_i^*, and land l_i^* as functions of idiosyncratic distortions τ_i^y, τ_i^k, τ_i^n and τ_i^l, parameters α, β, and γ, exogeneous factor prices R, w, and r, and farm-level productivity s_i. These suboptimal factor demand functions with distortions will be different from the social planner's efficient allocation of land and capital (i.e., k_i^e, n_i^e and l_i^e) across households within the village. Put these suboptimal factor demand functions (k_i^*, n_i^*, and l_i^*) back into the farm's production function, we will then obtain the suboptimal output supply function $y_i^* = s_i^{1-\gamma}\left(k_i^{*\alpha} n_i^{*\beta} l_i^{*1-\alpha-\beta}\right)^{\gamma}$ for each household. Using the fact that total output is $Y = \sum_i^I y_i$, it can be shown that the village-wide aggregate production function has the following form:

$$Y^* = TFP^* \cdot I^{1-\gamma}\left(K^{\alpha} N^{\beta} L^{1-\alpha-\beta}\right)^{\gamma} \qquad (A2.6)$$

which has a similar functional form for the social planner's output maximization problem Y^e, but $Y^* \neq Y^e$ since the former has a distorted aggregate TFP, TFP^*. Logically, we will have $Y^* < Y^e$ if any distortion exists. Recall that under the social planner's efficient resource allocation, we have $TFP^e = (\overline{s})^{1-\gamma} = \left(I^{-1}\sum_i^I s_i\right)^{1-\gamma}$. Here, with various types of distortion, we have

$$TFP^* = \left(I^{-1}\sum_i^I s_i\left(\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{\gamma}{1-\gamma}}\right)^{1-\gamma} \qquad (A2.7)$$

where $\overline{TFPR} \propto \left(\overline{MRPK}\right)^{\alpha}\left(\overline{MRPN}\right)^{\beta}\left(\overline{MRPL}\right)^{1-\alpha-\beta}$ is the *average* of our summary measure of distortion $TFPR_i$ across farms. Note that, if all distortions are eliminated, $TFPR_i$ will be a constant scalar, so will be its average $\overline{TFPR}$. In this situation, the above measure of TFP^* will be equivalent to TFP^e. As long as that $TFPR_i$ is not a constant, i.e., there are dispersions observed in $TFPR_i$, then $TFP^* \neq TFP^e$, and more specifically, we will have $TFP^* < TFP^e$ if any distortion exists. In this way, the gains in aggregate output and TFP from removing all distortions can be similarly defined as in the social planner's problem (see equation (2.7)).

With this profit maximization approach, we have several ways to detect the existence of resource misallocation directly or indirectly. First, we could measure the extent of resource misallocation by using the measured dispersion (e.g., standard deviation) in the marginal (revenue) product of factors. Recall that, for example, without land market distortion ($\tau_i^l = 0$) and output market distortion ($\tau_i^y = 0$), then $MRPL_i$ from first order condition should be equated across households and its standard deviation equals 0. How far the measured dispersion in $MRPL_i$ deviates from 0 can be used to measure the extent of land misallocation (Chen et al., 2021). $MRPL_i$ is calculated from the data set by noting that $MRPL_i = (1-\alpha-\beta)\gamma(y_i/l_i)$, where y_i and l_i are actual output and land input use, and y_i/l_i is the average product of land. The same applies to capital and labor.

Second, we can also measure the extent of misallocation by using the dispersion (standard deviation of $TFPR_i$ or standard deviation of $\ln TFPR_i$) of the revenue productivity $TFPR_i$ (see Adamopoulos et al., 2020 for further discussions). Without any distortions, $TFPR_i$ will be a constant scalar and hence its dispersion is also zero. Any deviation from the efficient zero dispersion can be used similarly to those of marginal revenue products of factors. This measure can be calculated from the data set by noting that $TFPR_i = y_i/(k_i^{\alpha} n_i^{\beta} l_i^{1-\alpha-\beta})$, where output and inputs are observed. Note that, using the dispersion of TFP^* has the similar usefulness given that if there were no distortions, $TFP^* = TFP^e$, which is constant toward the average farm-level productivity with zero dispersion. If there are distortions, the dispersion in TFP^* will be related to dispersion in $TFPR_i$ (see Hsieh and Klenow, 2009).

CHAPTER 3
DO SMALL FARM SIZES IMPLY LARGE FACTOR MISALLOCATION? EVIDENCE FROM WHEAT-MAIZE DOUBLE-CROPPING FARMS IN THE NORTH CHINA PLAIN*

ABSTRACT The egalitarian allocation of agricultural land and small farm sizes in rural China raises questions about the implications for overall productivity given that there exists potentially large heterogeneity in farm-level productivities. This chapter empirically examines to what extent land and capital are misallocated in a region of China that is characterized by small and relatively evenly distributed farm sizes. Using a survey data set collected from local wheat-maize double-cropping farms, we find that the dispersion in farm-level total factor productivity is small and the quantified gains in aggregate agricultural productivity that may be obtained by reallocating factors from less productive to more productive farms are moderate relative to findings in the previous literature. Estimated productivity (output) gains in the region range from 7% for within-village reallocation to 10% for between-village reallocation. We argue that these findings are largely explained by the relatively high-level use of hired machinery services in the region.

* This chapter is based the working paper:
Chen, M., Heerink, N., Zhu, X., & Feng, S. (2021). Do small farm sizes imply large resource misallocation? Evidence from wheat-maize double-cropping farms in China.

3.1. INTRODUCTION

The success of agricultural development in China since the 1980s and the associated major achievements in rural poverty reduction, structural transformation, and overall economic development have been largely attributed to the growth in aggregate agricultural productivity (see Cao and Birchenall, 2013; Ivanic and Martin, 2018; Ligon and Sadoulet, 2018). However, some recent studies find that the rate of growth of agricultural productivity (i.e., total factor productivity or TFP) has declined in recent years (e.g., Sheng et al., 2020; Gong, 2018). These findings cast doubt on China's potential to remain self-sufficient in food in the near future. The sluggish performance of agricultural productivity growth calls for public policies to refuel the growth engine.

One approach that has been stressed in the recent productivity growth literature is to foster productivity gains through reallocating productive factors toward more productive units (see reviews in Bartelsman and Doms, 2000; Tybout, 2000; Syverson, 2011; Restuccia and Rogerson, 2017). Such reallocations can be particularly relevant for the agricultural sector in developing countries where factor markets are often distorted by institutional arrangements that neglect differences in factor productivities between farms. In the case of China, agricultural land is collectively owned by villages and land use rights are allocated among villagers on an egalitarian basis. As a result, observed operational farm sizes tend to be very small and show little variation within villages. This may imply that large allocative inefficiencies (misallocation) of productive factors exist across farms for two reasons: first, equal land distribution contributes to land misallocation because farms are usually heterogeneous in their land productivities; and second, small average farm sizes may contribute to capital misallocation because small farms face relatively large barriers to capital markets (e.g., Adamopoulos et al., 2020).

Recent empirical evidence at the national level for China supports these implications. Adamopoulos et al. (2020), Chari et al. (2020), Gai et al. (2020), and Zhao (2020) found that productive factors such as land and capital are significantly misallocated across farms in China. The estimated gains in aggregate agricultural productivity that could have been obtained from efficient factor reallocation amount to 136% for the period 2004-2013 (Gai et al., 2017). Although these studies answered different important questions for different time periods, their findings and policy suggestions were mostly retrospective and may not fit the current situation of agricultural production. Moreover, and interestingly, all these studies are based on the same nationally representative household-level panel data set that was collected through the National Fixed Point Survey (see Benjamin et al., 2005 for a description), while evidence from alternative data sets is still missing. For these reasons, we identify two major gaps that still exist in the current literature.

First, in measuring capital input, the literature has not seriously considered hired machinery services (also referred to as mechanization outsourcing) among smallholders in China, mainly because it is only a recent trend (see Yang et al., 2013; Wang et al., 2016;

Wang et al., 2016; Sheng et al., 2017). Its implications on resource allocation and aggregate productivity are still unknown. Intuitively, the shift from relatively labor-intensive production toward the extensive use of hired machinery services in agriculture enables credit-constrained smallholders to reallocate agricultural labor to more productive activities, and thereby reduces the extent of capital and labor misallocation. In addition, the availability of machinery services can affect the demand for agricultural land on farms and generate an equilibrium distribution (allocation) of farm sizes that is different from what the literature suggests. Therefore, ignoring this machinery services cost may lead to severe mismeasurement in capital input, and the estimated magnitudes of factor misallocation and productivity gains can be misleading for policy implications.

Second, in addition to studies at the *national level*, research on factor misallocation and its implications for productivity gains at the *regional level* is needed as well. One reason is that different regions within a country can have different levels of factor misallocation (e.g., Zhu et al., 2011 for China; Ayerst et al., 2020 for Vietnam), and policy implications based on studies using nationwide data may have limited relevance in a large country like China that prefers gradual policy experiments on a narrower spatial scale (see Rozelle and Swinnen, 2004 and the references therein). Regional analysis may also deliver more accurate estimates of farm-level productivities by reducing the complexities involved in estimating national-level production functions. For example, to construct comparable farm-level productivities, the standard approach in the literature using nationwide data involves aggregating the production of multiple crops to the farm level and setting equal output elasticities in the production function. This method is applied even though the farms are in different agroclimatic zones and use fundamentally different cropping systems that are likely to be characterized by significantly different factor output elasticities.

Based on these considerations, this chapter aims to assess to what extent productive factors (land and capital) are misallocated in a relatively small region in China, characterized by a relatively equal distribution of land among smallholders and an increased use of hired machinery services in crop production. In particular, we exploit a household-level data set collected from four counties in Hebei Province, China. These counties are located within the North China Plain (NCP), a major agricultural production region of the country that is relatively homogeneous in terms of agro-environmental conditions. A large majority of farmers in the study area grow winter wheat and summer maize in a simple wheat-maize double-cropping system, as is the case throughout most areas of the NCP. The average operational farm size in the region is extremely small while the use of hired machinery services is extremely high; our data set indicates that approximately 90% of surveyed farming households use hired machinery services, especially in production activities such as land preparation, seeding, and harvesting (see more in Sections 3.2 and 3.3).

The quantitative framework that we use to assess factor misallocation follows closely the structural models adopted in previous studies that link micro-level productivities of heterogeneous farms to macro-level outcomes (see for example Restuccia and

Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Ayerst et al., 2020; Chen et al., 2021). Fitting our data to this framework, we find that the measured dispersions in farm-level productivities are small, implying that the misallocation of land and capital is small as well. Consequently, the potential gains in aggregate output and productivity from efficient land and capital reallocations within the region are also moderate. Although a direct comparison with findings in the literature should be cautious due to differences of data coverage in space and time, our findings robustly suggest that even if the operational farm sizes are extremely small, factor misallocation may not be as severe as the literature has indicated (e.g., in Adamopoulos et al., 2020; Chari et al., 2020). We argue that the major contribution to this lower-than-expected factor misallocation comes from the active use of hired machinery services among smallholders.

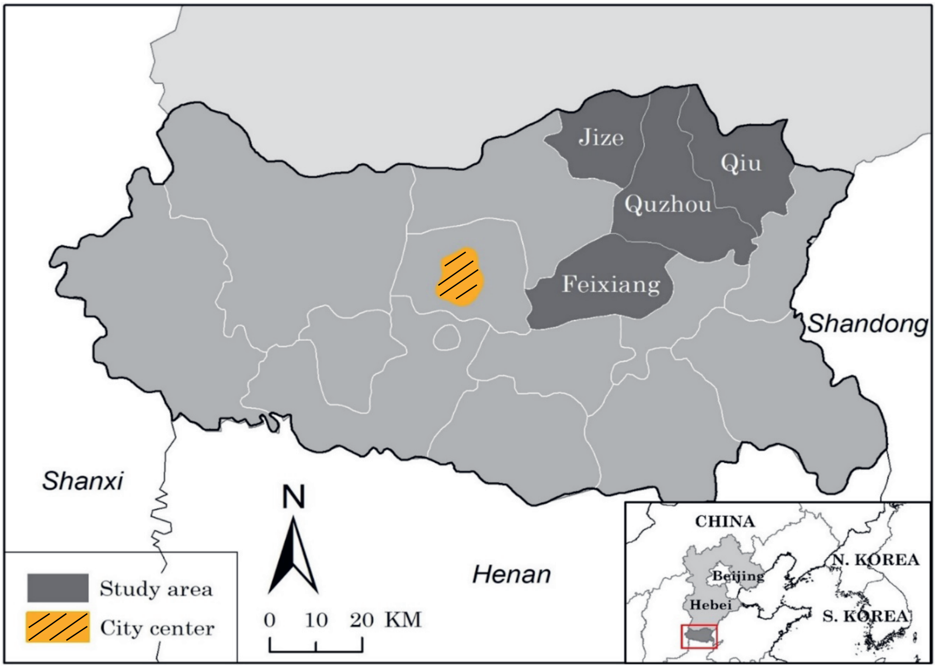
The rest of this chapter is structured as follows. In Section 3.2, a brief introduction of the study area is provided. We describe the survey data set in Section 3.3. In Section 3.4, we specify a quantitative model to explain how we assess factor misallocation. Section 3.5 examines and discusses the potential misallocation of land and capital for households in the survey data set. We conclude in Section 3.6.

3.2. BACKGROUND OF THE STUDY AREA

Our study area consists of four adjacent counties — Feixiang, Jize, Quzhou, and Qiu — in Handan Prefecture, Hebei Province, China (see Figure 3.1 for county locations). The official data from Handan Bureau of Statistics (HBS, 2018) showed that, by the end of 2017, the area had a total population of 1.34 million, of which 55% were rural residents, 12 percentage points higher than the rest of regions within the prefecture. The per capita gross domestic product (GDP) in the area was 30,395 yuan (about 4,500 US dollars, in current value), 15% lower than the prefecture average, and only about half of the national average. The GDP of the primary industry represented approximately 17% of the total GDP within the area, twice that of the remaining area in the prefecture and of the whole country. In the local agricultural sector, wheat and maize are the two most important crops, with 74% of all sown area devoted to them in 2017.

Most farms in the area grow a double-crop rotation between winter wheat and summer maize. The former is usually produced from early October to early June in the following year, while the latter is produced from mid-June to late September. This wheat-maize double-cropping system is also the main farming system in the North China Plain, a major agricultural production region of China that extends across Hebei, Henan, Shandong, Jiangsu, and Anhui; these provinces together produced more than 79% of total wheat output and 30% of total maize output for China in 2017 (NBS, 2018).

Figure 3.1. Location of the study area in Handan prefecture, Hebei Province, China



Map source: Author's own creation with ArcGIS.

The agro-environmental characteristics of local crop production are relatively homogeneous. For example, the entire area is located within a fluvial plain, with minimal change in elevation (usually between 30-50 meters) and land slope; annual average temperatures in 2016 and 2017 of these four counties are around 14~15 °C. Rainfall, however, shows much variation. In 2016, it ranged from 545 mm in Feixiang to 804 mm in Jize, while in 2017 it amounted to 284 mm and 355 mm, respectively, for these two counties (HBS, 2017, 2018). Historical average precipitation in this area is only around 500 mm per year, with most of the rainfall concentrated in the summer. Therefore, crop production, particularly during the winter wheat growing season, is heavily reliant on irrigation, using either surface water or ground water.

Although the area is relatively flat, most farms are extremely small. The average size of the operated farms in 2017 in these four counties varied between 5.8 and 9.5 mu (or equivalently 0.39 and 0.63 ha for 1 mu = 1/15 ha; HBS, 2018;). In recent years, labor-demanding activities such as land preparation, seeding, and harvesting are increasingly carried out by big machines, while other activities such as fertilization, pesticide spraying, and irrigation are mainly done by hand, facilitated by small agricultural tools such as electric sprayers and water pumps (Liu et al., 2020). Machinery used on small farms is largely outsourced from specialized machinery services providers, usually local third-party machine owners (e.g., other farms or farm cooperatives). Large farms may hire machine services from outside the area or rely on their own machinery.

3.3. DATA

The farm-level data that we used for this research was collected through a field survey in February 2018. The survey was designed and carried out under the umbrella of a larger project that studies farm size enlargement and its implications. In the sampling, we first selected 28 townships out of 33 in four counties; five townships were excluded because one was mainly composed of a minority ethnic population and the other four were county centers and were less involved in agricultural production. We then divided the selected townships into three groups based on the number of villages they contained, that is, townships with 1-10 villages, townships with 11-20 villages, and townships with more than 20 villages (villages specialized in cash crops such as cotton and grapes were excluded before we counted the number of villages in each township; see Qian et al., 2020). In the first group, two villages were randomly selected from each township, while 4 and 6 villages were selected similarly from each township in the second and third groups, respectively (see Liu et al., 2020). This gave us 135 villages that were specialized in wheat and maize production at the time of the survey. In the last step, approximately 16 households were randomly selected within each sampled village for face-to-face interviews.

We effectively surveyed 2,121 households. Of these, 1,955 households produced wheat, 1,947 households produced maize, and 1,920 households produced both crops in the 2016/17 season. As our study focuses on factor allocation among existing farms, we first drop 89 households that did not cultivate land last season. Then we drop another 240 households that reported different sown areas for wheat and maize and focus only on wheat-maize double-cropping households. The resulting sample includes 1,788 households.[15] For them, we have not only detailed quantitative information on crop-specific input and output quantities and prices, but also qualitative information on farm-specific soil types and irrigation conditions.

The average operational farm size (defined as the land area contracted from village collectives plus net rented land area) in the remaining sample equals 9.6 mu, while the median operational farm size is only 7.0 mu. Table 3.1 shows that approximately 56% of the households have a farm size ≤ 7.5 mu, almost 93% operate a farm size ≤ 15 mu, and approximately 1% of the farms have a size greater than 30 mu. On average, the households

[15] Note that, this number of households comes from dropping another four wheat-maize double-cropping households due to negative value-added (see more discussion in Section 3.5 and Appendix A).

in the sample use more than 88% of their operational land area for wheat-maize double-cropping. This share is highest for relatively small farms.

Table 3.1. Operational farm sizes and wheat-maize double-cropping land shares (N= 1,788)

Operational farm size range	Number of farms	Percentage	Average land share used for wheat-maize double-cropping
≤ 7.5 mu (0.5 ha)	1,010	56.49%	92.65%
7.5-15 mu (0.5-1 ha)	649	36.30%	85.26%
15-30 mu (1-2 ha)	110	6.19%	74.72%
30+ mu (2+ ha)	19	1.06%	52.49%
Total	1,788	100%	N/A

Source: Authors' own calculations.

Notes: For the whole sample (N=1,788), average operational farm size is 9.6 mu and median farm size is 7.0 mu. The average land share devoted to wheat-maize double-cropping is 88.4%.

Most farms in the sample use their own land contracted from village collectives to produce wheat and maize. Land rentals are relatively uncommon among the interviewed households; only 12.5% of them reported land rent-in and 11.4% reported land rent-out in 2017. Even if we include the households that have been dropped (i.e., a full sample of 2,121 households), the land rent-in percentage merely increases to 12.7% and the land rent-out percentage increases to 15.2%.[16] As a comparison, the percentage of farming households reported land rent-out for the whole country equaled 30% in 2016 (MOA, 2017).

Hired machinery services are very common especially in the production stages of land preparation, seeding, and harvesting (see Table 3.2). For both wheat and maize production, approximately 90% of households used hired machinery services in these stages. In other activities, including fertilization, agrochemicals spraying, and irrigation, labor and own machinery are more commonly used. The relatively high percentages of own machinery use in irrigation, about 45% in both wheat and maize production, are mainly due to the inclusion of water pumps that many local households possess, even though their value may be negligible in capital formation. In all stages of production, family labor is the dominant form of labor input; it accounts for approximately 96% of total labor input in wheat and maize production.

[16] We particularly conducted the field survey right after the Chinese lunar new year, when most family members are at home, to avoid large replacements in random sampling. But to the extent that some agricultural households in the study area might have moved entirely and permanently to the urban sector and were not reflected in the name list that we used to do sampling, the renting-out percentage in our sample may be slightly underestimated.

Table 3.2. Share of households that use machines in wheat and maize production stages (N = 1,788)

Production stages	Wheat		Maize	
	Hired machine	Own machine	Hired machine	Own machine
Land preparation	89.03%	5.93%	90.27%	4.31%
Seeding	92.17%	5.20%		
Fertilization	6.94%	1.51%	10.46%	1.06%
Agrochemicals spraying	0.50%	7.33%	0.73%	12.53%
Irrigation	8.61%	45.97%	8.78%	44.02%
Harvesting	92.84%	4.36%	80.59%	3.30%

Source: Authors' own calculations.

Notes: In maize production, land preparation and seeding are preformed simultaneously with machine, and we use a single value for both production stages.

3.4. CONCEPTUAL FRAMEWORK

To empirically assess to what extent production factors are misallocated across these wheat-maize double-cropping farms, we closely follow Restuccia and Santaeulàlia-Llopis (2017) and Adamopoulos et al. (2020). We consider a rural economy that is endowed with a total amount of agricultural land L, farm capital K, and a finite number of farms M indexed by i. A farm is a production unit managed by an operator who uses farming skills and production factors that are under his control to produce agricultural goods. Farm operators are assumed to be heterogeneous in their ability s_i in managing the farm. The farm-level production function features a "span of control" (see Lucas, 1978) that has constant returns to scale for production technology and diminishing returns to scale for managerial skill:

$$y_i = s_i^{1-\gamma}\left(l_i^{\alpha} k_i^{1-\alpha}\right)^{\gamma} \tag{3.1}$$

where y_i is the output of farm i; l_i is land input, and k_i is capital input. The parameter α captures the relative importance of land input in the production process; $\gamma < 1$ is the parameter of "span of control" that governs the returns to scale at farm level. For reasons of simplicity, equation (3.1) abstracts away from labor input differences across farms. We return to this abstraction and discuss its validity in Section 3.5.1.

The behavioral assumption about the social planner of the economy is to decide how to allocate land and capital across farms to maximize aggregate output $Y = \sum_i y_i$, given farm-level production technologies in equation (3.1) and total resource endowments of the economy $\sum_i l_i = L$ and $\sum_i k_i = K$. Constrained optimization leads to a unique scheme of efficient allocations of land and capital as follows:

$$l_i^e = \frac{s_i}{\sum_{i=1}^{M} s_i} L;\ k_i^e = \frac{s_i}{\sum_{i=1}^{M} s_i} K; \tag{3.2}$$

where the superscript e represents efficient allocation. Equation (3.2) implies that, in the static equilibrium, the social planner allocates land and capital according to farms' *relative* productivities ($s_i / \sum_{i=1}^{M} s_i$) in the economy, and the more productive farms will be allocated more resources. Under this allocation scheme, the distributions of factor inputs across farms will be non-degenerating because the most productive farm does not possess all resources. This feature is inherently embedded in the assumption that the farm-level production function exhibits diminishing returns to scale in managerial skills, i.e., the "span of control" parameter $\gamma < 1$. Adamopoulos and Restuccia (2014) emphasize that these theoretically derived equilibrium distributions are consistent with the observed distributions of agricultural land and capital use in the real world, where farms that are heterogeneous in their farming ability coexist in the same production system. In general, equation (3.2) indicates that the cross-farm distribution of land and capital should be strongly positively correlated with the distribution of farm-level productivities, and any deviation between the two distributions would suggest the potential existence of factor misallocation.

To quantify the impact of non-zero factor misallocation on aggregate agricultural output, we first substitute equation (3.2) into $Y = \sum_i y_i$ to derive the aggregate production function under efficient resource allocation. This gives,

$$Y^e = TFP^e \cdot M^{1-\gamma} \left(L^{\alpha} K^{1-\alpha}\right)^{\gamma} \tag{3.3}$$

where Y^e is the aggregate output level under efficient factor allocation; $TFP^e = (\overline{S})^{1-\gamma}$ measures aggregate productivity, and $\overline{S} = M^{-1} \sum_i^M s_i$ is the average farming ability of the M farms. The potential gain in aggregate output then can be quantified by contrasting this efficient aggregate output with the actual aggregate output. If the factors are misallocated, the output gain is positive. Given that total resource endowments L and K and the total number of farms M in the economy are assumed to be fixed, the potential gain in output is also the potential gain in aggregate productivity.

3.5. EMPIRICAL APPLICATION

To bring the quantitative framework to data, we construct farm-level total factor productivity (TFP) residually from farm i's production function in equation (3.1):

$$TFP_i \equiv s_i^{1-\gamma} = \frac{y_i}{\left(l_i^{\alpha} k_i^{1-\alpha}\right)^{\gamma}} \tag{3.4}$$

This definition of TFP relates only to the farming ability s_i and can be interpreted as a physical productivity, which measure, in the first place, requires data of real output and input that do not reflect price effects (see for example Foster et al., 2008; Hsieh and Klenow, 2009), and in the second place and particularly for agricultural production, requires data that are not confounded by observed and unobserved farm-level heterogeneities such as transitory shocks and land quality (see e.g., Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Gollin and Udry, 2021).

3.5.1. Measuring farm-level productivity and productivity dispersions

We use the data set described in Section 3.3 to construct farm-level output y_i, land input l_i and capital input k_i in equation (3.4). In particular, farm output is measured by value-added that subtracts "real" costs of intermediate inputs from the "real" gross output of wheat and maize; land input is measured by the land area devoted to wheat-maize double-cropping. A key difference between this chapter and the previous literature is the measure of capital input. In particular, we rely heavily on the cost of hired machinery services to measure capital input, while also adding in the imputed own machine use cost. In Appendix A, we describe in detail the methods of variable construction.

It is important to note that the specification of the production function in equation (3.1) (and therefore also the farm-level TFP in equation (3.4)) implicitly assumes that labor input is the same across farms, while in the data set farms differ in their labor inputs. Following the convention in the literature (see Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Chen et al., 2021), we normalize y_i, l_i and k_i and express them in unit labor input. Such a construction implies that we ignored the potential misallocation of labor across farms, and therefore the estimated misallocation could be conservative if labor misallocation were huge. However, this ignorance might be justified given that farming activities in our study area were done mostly by family labor (accounts for 96% of total labor input; see Section 3.3) that cannot be effectively reallocated across farms in practice (see Chen et al., 2021).

Measuring farm-level TFPs also requires information on the parameters α and γ. The capital income share for each farm is calculated as the ratio of capital input to farm output. We take the median value as the measured capital income share, which gives $(1-\alpha)\gamma = 0.205$. Computing the land income share requires farm-level cost estimates of land input. The data set contains only limited information on land rental prices due to the relatively small number of land rental transactions (see Section 3.3), and therefore, we use the average land rental price published by the Handan municipal government one month before our field survey, which was 417.4 yuan per mu (HMDRC, 2018). We apply this common price to all operated land (rented and contracted) and compute the land income share for each farm as the ratio of land input cost to farm output. The measured land income share is obtained, again, by taking the median of these farm-specific ratios, which implies $\alpha\gamma = 0.318$. Given these estimated values, we derive $\gamma = 0.523$, which implies a labor income share of $1 - \gamma = 0.477$. In general, our estimated factor income shares, which are 0.205, 0.318, and 0.477, respectively, for capital, land, and labor, are virtually similar to those used in Adamopoulos et al. (2020) for China (0.18, 0.36, 0.46, respectively). However, they are very different from that Restuccia and Santaeulàlia-Llopis (2017) used to study Malawian agriculture (0.36, 0.18 and 0.46, respectively). In Appendix B, we show that our main findings in the following sections are generally very robust to these alternative calibrations of factor income shares.

The above information allows us to compute farm-level TFPs using equation (3.4). But such a measure may still be confounded by differences among farms in land quality, weather shocks, and other unobserved heterogeneities. For example, if a farm had a higher quality of land and experienced a positive weather shock, then we probably overestimated its farm-level TFPs. To address this concern, we follow Adamopoulos et al. (2020) and further estimate the component of farm-level productivity that is unconfounded by these factors by regressing (without a constant) the foregoing log farm-level TFPs on farm-level soil types (as an indicator of soil quality), irrigation conditions, and village-level fixed effects. We include irrigation conditions because precipitation is relatively low in the study area and crop production is highly dependent on irrigation. We do not explicitly control for other heterogeneities, for instance, land slope and erosion, because they are less important in a region that is relatively homogeneous in its agro-environment (see Section 3.2). This gives the following specification:

$$\ln TFP_{iv} = \beta_1 \times irrigation_{iv} + \beta_2 \times soil\_type_{iv} + \sum_v \delta_v \times village_v + \epsilon_{iv} \tag{3.5}$$

The variable "$irrigation_{iv}$" represents the irrigation condition of farm i in village v, as assessed by the farmer. It ranges from 1 (worst) to 5 (best). The variable "$soil\_type_{iv}$" is categorical in that it measures three types of soil, i.e., sandy, clay, and loam. The variable "$village_v$" represents village fixed effects. The parameters to be estimated are β_1, β_2, and δ_v, and ϵ_{iv} is the error term. Village fixed effects are added for two reasons: first, self-evaluated irrigation conditions may only have reflected *relative* conditions within villages; second, the variation in farm-village specific TFPs may also contain other unobserved village-specific effects such as external technology interventions.[17] We use the regression residuals from equation (3.5) to measure the (log) physical productivity at the farm level, which is,

$$\ln \widehat{TFP}_{iv} = \ln TFP_{iv} - \widehat{\beta_1} \times irrigation_{iv} - \widehat{\beta_2} \times soil\_type_{iv} - \sum_v \widehat{\delta_v} \times village_v \tag{3.6}$$

[17] Some villages in our sample are selected by the so-called Science & Technology Backyard program as pilot sites for production experiments. See Li et al. (2020).

Column (1) and (2) in Table 3.3 summarizes several dispersion measures of this log farm-level TFPs. In column (1), which is based on a full sample of 1,788 observations, the standard deviation of the estimated farm-level TFPs (in log terms) is 0.57. The log TFP difference between the 75th and 25th percentiles (p75-p25) is 0.56, implying that farms at the 75th percentile are $e^{0.56}$= 1.75 times more productive than farms at the 25th percentile in the distribution. The log differences between other paired percentiles range from 1.14 to 2.55. In column (2), we trimmed 16 extreme outliers from the distribution.[18] As expected, the standard deviation and log TFP difference between the 99th and 1st percentile farms reduced significantly after deleting these extreme values, while the other dispersion measures are fairly robust.

Table 3.3. Dispersions of farm-level TFPs

	(1) This study (Full sample)	(2) This study (16 extreme values excluded)	(3) Adamopoulos et al. (2020)	(4) Restuccia and Santaeulàlia-Llopis (2017)	(5) Ayerst et al. (2020)
Country	China	China	China	Malawi	Vietnam
Data coverage	Regional	Regional	National	National	National
Data period	2016/2017	2016/2017	1993-2002	2010/11	2012-2016
Std. Dev.	0.57	0.44	0.35	1.19	0.58
p75-p25	0.56	0.56	1.48	1.15	---
p90-p10	1.14	1.12	2.18	2.38	---
p95-p5	1.47	1.43	---	---	1.88
p99-p1	2.55	2.06	---	---	2.74
N	1,788	1,772	6,000+	7,157	2,087

Notes: all dispersion measures are in logarithmic terms. "Std. Dev." is the standard deviation. "p75-p25" is the difference between 75th and 25th percentiles in the distribution of log TFPs. A similar definition applies to other dispersion measures in the table. In column (2), we trimmed 16 extreme values (see footnote 18 for definition).

Productivity dispersion measures obtained by Adamopoulos et al. (2020) for farms in China during the period of 1993-2002 (column (3)) and by Restuccia and Santaeulàlia-Llopis (2017) for farms in Malawi in the 2010/2011 season (column (4)) have almost double the values that we obtained in our study, even though the former study estimated a lower

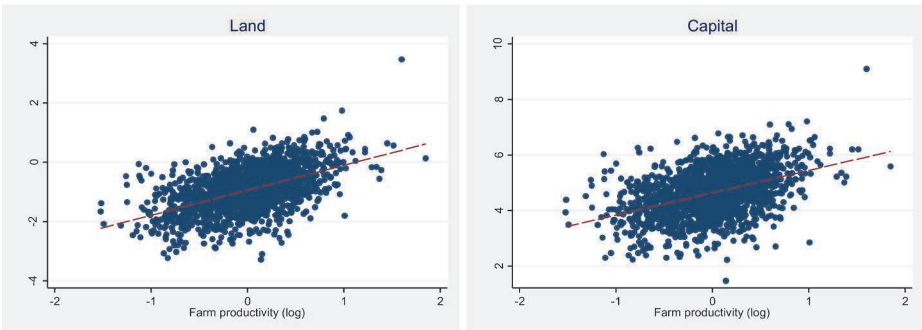
[18] We define extreme outlier as a value that is either larger than $p75 + 3 \times (p75 - p25)$ or smaller than $p25 - 3 \times (p75 - p25)$, where $p75$ and $p25$ are respectively the 75th percentile and the 25th percentile of the log TFP distribution. The trimming involves two farms from the lower tail and 14 farms from the upper tail. Interestingly, the latter all come from one single village in Quzhou County.

standard deviation. Our measured dispersions are closer to those found by Ayerst et al. (2020) for China's neighboring country Vietnam during 2012-2016 in column (5), which has a system of rural land allocation in the north that resembles the Chinese system. Note that, however, the comparison between our study and the above studies should be cautious, as the estimated gaps may be driven by differences of data coverage in time and space, instead of the inclusion of hired machinery services in capital measure. We discuss this important question in Section 3.5.3.

3.5.2. Factor misallocation and aggregate productivity gains

Based on the distribution of estimated farm-level TFPs, we empirically assess to what extent factors are misallocated in our study area with the two approaches suggested in Section 3.4. We first visually contrast the distribution of observed factor inputs to the distribution of measured farm-level TFPs, and then we quantify the static efficiency gains in aggregate output (or productivity) from efficient resource allocation.

Figure 3.2. Land and capital allocation across farms with different productivities



Notes: log farm productivity is estimated from equation (3.6) and the data trimmed 16 extreme values (1,772 observations remain; see footnote 18). Land and capital are measured in terms of labor days. The dashed lines are the estimated relationship between inputs and productivity; the left (land) and right (capital) panels have estimated correlation coefficients of 0.52 and 0.43, respectively.

To start, note that equation (3.2) implies that, under efficient allocation, factor inputs should be strongly positively correlated with the measured farm-level TFPs. If, however, the cross-farm correlation between the observed factor input (land, capital) and the measured farm-level productivity is small, then there may exist factor misallocation. The extent of misallocation is larger when the correlation coefficient is smaller. Figure 3.2 shows that there is a virtually significant positive relationship between the distributions of log land inputs (or log capital inputs) and log farm-level TFPs (both are measured per labor day). When these are put in numbers, the correlation coefficients are 0.52 and 0.43 in the left and right panels, respectively. By contrast, Restuccia and Santaeulàlia-Llopis (2017) find for Malawi that these correlation coefficients are equal to 0.05 and -0.01, respectively; their findings imply little correlation and therefore strong misallocation in land and capital in that country. Adamopoulos et al. (2020) find similar evidence for China that land and capital are severely misallocated across the country. They even find a more negative correlation, as is evident in their visualized graphs, between capital input and farm productivity, implying a much more severe capital misallocation in China.

An additional (indirect) measure of resource misallocation can be obtained by quantifying aggregate output gain from efficient resource allocation. Intuitively, if the extent of factor misallocation is small, the static gains in aggregate output or productivity obtained from efficient resource allocation will also be small. We use the aggregate production function specified in equation (3.3) and measure the gain as the percentage change between efficient aggregate output level to the actual aggregate output level (e.g., Chen et al., 2021):

$$Aggregate\ Gains = \frac{Y^e - Y^a}{Y^a} = \frac{Y^e}{\sum_i y_i^a} - 1 \qquad (3.7)$$

where Y^e denotes the aggregate output level when factors are efficiently allocated according to equation (3.2); Y^a is the aggregate output level observed in the data set. To make them comparable, we use measured physical productivity to compute both Y^e and Y^a. Note that, since total resource endowments and the number of existing farms are assumed fixed in the economy, the percentage gain in aggregate output in equation (3.7) also imply the percentage gain in aggregate productivity.

Table 3.4. Efficiency gains from resource reallocation within and across villages

	Gains
Eliminating land and capital misallocation across households:	
within villages	7.03%
within and across villages	9.87%

Source: Author’s own calculations.

Note: Gains are based on the trimmed sample of 1,772 farms.

Table 3.4 presents the results of two hypothetical efficient resource reallocation experiments: one is to reallocate within villages, and the other is to reallocate within and across villages. The estimated gain in aggregate output (productivity) from efficient reallocation of land and capital *within* villages equals 7.03%, while that from reallocation *within and across* villages equals 9.87%. The magnitudes of both gains confirm our findings in Figure 3.2. They are much smaller than the gains estimated by other studies for China. For example, in Adamopoulos et al. (2020), the estimated efficiency gains equal to 24.4% for within-village reallocation and 53.2% for within- and between-villages reallocation. Chari et al. (2020) focus on the period between 2003-2010 and perform an exercise similar to Adamopoulos et al. (2020) and find that if all misallocation of land were eliminated, aggregate output in China during that period of time would increase by 73%. We note that comparison across these studies may be misleading given the differences in data coverage, variable measurements, and other relevant issues. What we would like to stress from our findings is that even though the local operational farm sizes are extremely small and the land rental market is mostly inactive, the estimated gains in aggregate output and productivity are much lower than one would expect from the literature.

3.5.3. Discussion

What might explain these moderate gains in aggregate production? One explanation is the fact that our survey was conducted in a relatively small region with farms expected to be less heterogeneous in their productivities than in the case with nationwide analyses (that characterize most of the previous literature). However, this cannot be tested without a data set that directly extends our study area to a larger area. Another explanation is the role played by quasi-fixed inputs, particularly land and physical capital, in the region. In this subsection, we focus on this latter explanation, starting with a discussion of the local land rental market, and subsequently focusing on the market for hired machine services.

In the land market, when major market imperfections exist, transfers of agricultural land from less productive farms to more productive farms will be limited, and result in wedges in marginal products of land across farms (see for example Le, 2020; Adamopoulos and Restuccia, 2014; Chen et al., 2021). In China, land ownership in rural areas rests with the village collective. Although there is no land sales market, the land rental market has been growing quickly over the past 20 years; the ratio of transferred land area to total contracted land area increased from less than 3% in 1997 to about 35% in 2016 (see Brandt et al., 2002; MOA, 2017). However, land rental transactions are less common in our study area, despite the fact that operational farm sizes are extremely small (see Section 3.3). Based on findings from the recent literature, these characteristics likely lead to conclusions that local land is severely misallocated and government efforts to promote land consolidation through land transfers in the region can be highly rewarding. However, our analyses show that reallocating land further from less to more productive farms provides a limited contribution to increased aggregate agricultural output and productivity in the region; the estimated gains presented in Table 3.4 provide upper limits for eliminating both land and capital misallocation, and therefore gains from only land reallocation are likely to be even lower.

If land rental transactions do not explain the relatively efficient allocation of land in our study area, then what else might explain it? Note that equation (3.2) implies that, under efficient resource allocation, one of the necessary conditions of efficient resource allocation is to equate capital-land ratios across farms to a constant K/L. Intuitively, two types of adjustment make such equalization possible: by land rentals in the land market or by machinery services in the capital market. When the land market is not functioning well to reduce distortions to capital-land ratios, the emergence of a capital rental market can facilitate this equalization (see Ray, 1998, Chapter 11). Using hired machinery services may reduce misallocation of land by allowing smallholders to flexibly adjust their capital input to a given quantity of land.[19] It may also facilitate the convergence of productivities among farms of different sizes by diffusing production technologies used on larger farms, or other machinery services providers, to smallholders.

However, one must note that the equalization of capital-land ratios across farms is not a sufficient condition for efficient resource allocation. To test to what extent the estimated low level of misallocation is due to the inclusion of hired machinery services, two empirical approaches can be explored: First, one may completely ignore hired machinery services in crop production and simply replace the flow cost measure of capital input in our study with the traditional measure of capital stock owned by farms, using current or perpetual inventory methods. Second, one may still take hired machinery services into account, but by considering it as an intermediate input and, therefore, subtract it from farm-level gross output. Then capital input in the left-hand of equation (3.1) is measured by capital stock. These updated measures of variables can then be applied to re-estimate factor income shares and farm-level TFPs, and to evaluate the extent of factor misallocation by following the same procedures as in Section 3.5.1 and 3.5.2. However, due to data limitations on capital stock measures,[20] we leave this important question for future studies.

3.6. CONCLUSION

In this chapter, we explored a farm-level data set collected in the North China Plain and found that land and capital are only moderately misallocated across the surveyed wheat-maize double-cropping farms. This might be counterintuitive, especially when we observe

[19] However, on the other hand, Chari et al. (2020) find that land reform (or efficient reallocation of land) does not significantly increase the input intensity of capital at household level, measured either by the total value of farm-owned agricultural assets (capital stock) or by the costs of operating the machinery, in terms of oil, fuel use, etc.

[20] Our data set only recorded the current values of several agricultural machines (including tractors, land ploughing and seed-sowing machines, crop management, irrigation and harvesting machines, and others) at the household level by asking the farmers to evaluate about how much money they could earn if they sold the machines on the market. Surprisingly, approximately 73% of sampled households reported no owned agricultural machinery, and thus led to zero capital stock. We believe this was primarily because of two reasons: First, many households did not own machines, and they mostly rented from others. Second, the value of agricultural tools owned by these households was too small, and therefore many households chose not to value and report them at all. These features may cause severe measurement error in capital stock.

small and relatively equally distributed farm sizes in the local area. Our finding suggests that improving local agricultural output and productivity through efficient resource reallocation, though possibly effective, has only moderate impact. We explain this finding from the fact that local farms are relatively homogeneous in their productivities due to the use of hired machinery services by most farmers.

These findings also have important policy implications. While the key policy suggestions of most previous studies are to remove institutional barriers in the land market, stimulating efficiency by reallocating land to the most efficient farmers can face great social and political challenges in developing countries, including China, as agricultural land may also play important risk-reducing roles by providing food security and social safety nets to rural households. In such cases, fostering allocative efficiency through other factor markets, for example, capital, can be a plausible alternative for policy design since factor markets are often interlinked, and improvement in the functioning of capital market would contribute to the equalization of capital-land ratios and hence to increased aggregate output and productivity.

Our findings may also be considered as an echo of the recent discussions in Fuglie et al. (2020) that agricultural land may not be as misallocated as the literature has suggested in developing regions, and the emergence of smallholder-friendly new technologies (e.g., minitractors combined with leasing market) has made small plots farming highly productive; countries with equitable land allocation are found to be associated with higher land productivities (see Vollrath, 2007). Moreover, it can also be consistent with the recent findings in Cusolito and Maloney. (2018), who analyzed firm-level manufacturing data in six countries (Chile, China, Columbia, Ethiopia, India and Malaysia), and showed that the main engine for aggregate productivity growth in the manufacturing industry is still technological progress; for China, the contribution of improved firm performance (within-component) explains approximately 60% of overall productivity growth in the manufacturing sector while that of improved factor allocation across firms (between-component) and firm entry and exit, respectively, accounts for about 20%.[21]

Our study is not free of limitations. We particularly discuss two of them here. First, a key assumption in estimating the static productivity gains is that total resource endowments, i.e., land, capital, and the number of farms, remain fixed. For a regional study, this can be problematic to the extent that resources are also being reallocated across regions. For agricultural land, this seems to be a reasonable assumption, since agricultural land is usually rented in and out within the same village and occasionally within the same region due to administrative restrictions, cultural differences, and other factors. Machinery services are often provided locally but can also be provided by third parties from outside the region (see for example Yang et al., 2013). In the latter case, the assumption of fixed total

[21] Chari et al. (2021) and Wang et al. (2020) find that farm entry and exit have little effect on aggregate agricultural productivity improvement in China.

capital endowment in the region no longer holds. Unfortunately, our data set does not contain information about the sources of hired machinery services. Further research may explore to what extent this assumption is violated, and if so, its consequences for the main conclusions that we obtain in this study. Second, although we found that aggregate output or productivity gains from land reallocation are small, one should not downplay the importance of improved land market institutions for other purposes. Better functioning land institutions may contribute, for instance, to farm entry and exit through cross-sectoral resource reallocation or to incentivizing long-term agricultural investments. Since these are not the aim of this study, we leave them to future research.

APPENDIX A: MEASUREMENT OF FARM-LEVEL OUTPUT AND INPUTS

Real value-added

The data set contains farm-specific information on wheat and maize output quantities (in kg) and farm-gate prices (in yuan/kg). Price information is missing for some farms and crops as no market transactions occurred in the 2016/17 season. We imputed these missing prices by calculating the average of the observed prices received by interviewed households living within the same village. For wheat, 106 missing prices out of 1,955 households (or 5.42%) are replaced; and for maize, it involves 64 missing prices out of 1947 households (or 3.29%).

We use the output and price information to compute "real" gross output for each farm. To do so, the standard approach in the literature is to use crop-specific common prices (e.g., sample mean or median) to value output quantities, such that monetary values can better reflect "real" or physical variations in outputs (see for example Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Chen et al., 2021). In this chapter, we do not adjust for common prices for wheat and maize output. The reason for this choice is that the price variations observed in our data set largely reflect differences in output qualities, such as product moisture degree, the share of foreign materials and unsound kernels, and maize cobs vs. kernels. Moreover, cross-farm price variation is unlikely to be confounded by differences in, for instance, market powers or speculative opportunities given that the survey was held among smallholders living in a relatively small and homogenous region.[22]

We measured farm-level "real" cost of intermediate inputs, that is, seeds, fertilizers, and agrochemicals (pesticides/herbicides), by aggregating crop-specific costs of each input to the farm level. The survey only asked about the crop-specific total cost for each intermediate input used, primarily because its qualities (sometimes also quantities) are difficult to measure in practice, while market prices may vary significantly for different quality products. For example, different types of compound fertilizer are used in our study area, but farmers can hardly recall the fertilizer type that they bought.[23] The problem is most eminent for agrochemicals, due to the great diversity of products used and their

[22] Observed output price variations in our dataset are also unlikely significantly influenced by price seasonality. Although there were nine months between wheat harvest and our survey time (June 2017-February 2018), official data indicates that wheat price during that period only increased by less than 6% from 2.47 yuan/kg to 2.61 yuan/kg. Maize price in the five months between its harvest and our survey time (October 2017-Februray 2018) was also quite stable and increased by approximately 3% from 1.9 yuan/kg to 1.96 yuan/kg (see China Yearbook of Agricultural Price Survey, 2019).

[23] For fertilizer type, we mean the total and separate percentages of nutrients component (nitrogen, phosphate, potassium) in the compound fertilizer. For example, one type of compound fertilizer may contain 45% of total nutrients, with N, P, and K respectively accounting for 15%, 15%, and 15%, while another type of compound fertilizer may still contain 45% of total nutrients, but with N, P, and K respectively 20%, 15%, and 10%. These two are usually priced differently and should be taken as different fertilizer types.

prices. In addition, a narrowly defined study area can help reduce the possibility that cost variations are due to market conditions.

"Real" value-added is calculated by subtracting total intermediate inputs cost from the gross output value. This resulted in four negative values, which we dropped. Though negative values are allowed in the construction of equation (3.4), dropping them would simplify our data analyses and follow-up interpretation, and would not seriously affect our results and conclusions, as the number of negative values are small. As a result, 1,788 households were used for the analysis.

Land and labor

The land area is measured by the cropland area planted with wheat or maize in the 2016/2017 season. The input of labor in the data set is recorded in terms of labor days. This distinguishes between family labor (including labor used for supervision) and hired labor for each crop in six production stages: land preparation, seeds sowing, fertilization, agrochemicals spraying, irrigation, and harvesting. To compute total labor input, we aggregated labor inputs over the two labor types, six production stages, and two crops.

Capital

Capital input is measured by total expenditures on machine services. The data set contains rich information on cost of hired machinery services per unit of land. We argue that the variation embedded in these unit costs is a good reflection of real cost differences due to farm location, land fragmentation, and other physical differences in production. We also use this unit cost information to impute the flow cost of own machine use based on the land size that uses own machine. In our study region, it is unlikely that a household uses machines (including both hired and own) only on the part of his sown area of wheat and maize, while using labor on other parts. Still, there are 37 households that did not use machines at all in production, most of which have small farm sizes and hence may use labor and other small tools to substitute machines. We impute the capital input for these households by using the average unit capital cost from the lowest 10% of farms that reported to use machines, which is approximately 89 yuan/mu.[24] A robustness check by dropping these 37 observations shows that our results are not significantly affected by this approach.

APPENDIX B: ROBUSTNESS CHECK WITH ALTERNATIVE FACTOR INCOME SHARES

[24] Alternatively, the imputation approach used in Adamopoulos et al. (2020) and Chen et al. (2021) is to assign each household a value equal to their operational farm size multiplied by 10% of the median capital-to-land ratio.

In this Appendix, we test if our TFP dispersion measures and the subsequent assessment of factor misallocation are sensitive to alternative factor income shares. Column (1) of Table B.3.1 replicates our results in the main text, with capital and land income shares equal to 0.205 and 0.318, respectively (see column (2) in Table 3.3). As a comparison, in column (2), we alternatively use the income shares 0.18 and 0.36, respectively, for capital and land. These numbers are estimated by Adamopoulos et al. (2020) for the period 1993-2002 in China and are quite close to our own estimates. In column (3) of Table B.3.1, the income shares we use are 0.36 and 0.18, respectively, for capital and land. These shares were adopted by Restuccia and Santaeulàlia-Llopis (2017) to study Malawian agriculture. What Table B.3.1 reflects is that, in either case, our measured TFP dispersions and measured factor misallocations are not sensitive to these alternative calibrations of factor income shares.

Table B.3.1. Farm-level TFP dispersions, correlation coefficients, and gains in aggregate output (productivity) with alternative factor income shares

	(1) This study	(2) Income shares from Adamopoulos et al. (2020)	(3) Income shares from Restuccia and Santaeulàlia-Llopis (2017)
Income shares			
Capital income share	0.205	0.18	0.36
Land income share	0.318	0.36	0.18
Farm-level TFP dispersions			
Std. Dev.	0.44	0.43	0.42
p75-p25	0.56	0.54	0.54
p90-p10	1.12	1.11	1.07
p95-p5	1.43	1.43	1.42
p99-p1	2.06	2.06	1.98
Correlation coefficients			
Corr (log land input, log TFP)	0.52	0.51	0.52
Corr (log capital input, log TFP)	0.43	0.42	0.39
Eliminating land and capital misallocation across households			
within villages	7.03%	7.44%	7.67%
within and across villages	9.87%	10.37%	10.60%
N	1,772	1,772	1,772

Notes: all dispersion measures are in logarithmic terms. "Std. Dev." is the standard deviation, and "p75-p25" is the difference between 75th and 25th percentiles in the distribution of log TFPs. Similar definition applies to other dispersion measures in the table. In all columns, extreme values (see footnote 18 for definition) were dropped.

CHAPTER 4
THE IMPACT OF LAND CERTIFICATION ON FACTOR REALLOCATION AND INTRA-VILLAGE INCOME INEQUALITY IN CHINA*

ABSTRACT This chapter examines the impact of a land certification program on rural households' land rentals and migration, as well as intra-village income inequality. Using household-level and village-level survey data sets collected in 2019 in three provinces in China, we measure the key explanatory variable as the number of years the program has been completed in villages and, therefore, are able to capture the impact of the program over time. We estimate that the program has a significant inverted U-shaped impact on households' probability of renting in land. Nonetheless, the study finds no statistically significant evidence that the program affects households' decisions of land renting-out and migration, nor does the program significantly affect intra-village income inequality. These findings are robust to alternative measures and estimation strategies.

* This chapter is based on the working paper:
Chen, M., Ren, G., & Heerink, N. (2021). The impact of land certification on factor reallocation and intra-village income inequality in China.

4.1. INTRODUCTION

The presence of a large misallocation of productive factors in the agricultural sector is considered an important source of low productivity and living standards in many agriculture-based developing countries (Caselli, 2005; Gollin et al., 2014; Restuccia and Rogerson, 2017). Recent evidence has shown that well-defined and secure land tenure rights can play a crucial role in facilitating efficiency-enhancing reallocation of land and labor both within agriculture and across sectors (see for example de Janvry et al., 2015; Chen, 2017; Chen et al., 2021). In the case of China, empirical evidence of such processes has been documented for the Rural Land Contracting Law (RLCL), which became effective in 2003 (see Zhao, 2020; Chari et al., 2021). While the RLCL intended to secure the land rights of farming households, promote land rentals, and restrict village-level administrative land reallocations, it lacked support from an effective system of land certificates that document the land rights held by rural households. The new land certification program rolled out across the country during the period 2009-2018 intended to formalize such rights by measuring, registering, and certificating farmers' agricultural land contracted from village collectives.

The recent literature has attempted to link this new certification program to the reallocation of factors across farms. For example, Cheng et al. (2016) and Wang et al. (2018) analyze subsamples of the 2012 China Health and Retirement Longitudinal Study data set and find that the program significantly increased the renting out of land by rural households; Zhang et al. (2019) use a survey data set collected by China Center of Agricultural Policy in 2016 and find that the program had a significantly positive impact on the renting-in of land by farmers. Gao et al. (2021) exploit the two-round household panel data set (2015 and 2017) in the Chinese Family Database; they find that the program significantly reduced land misallocation by increasing the land renting-out probability of farms with low productivities and the land renting-in probability of farms with high productivities. Their study also documents that households with low agricultural productivities were more likely to have at least one migrant member.

The studies mentioned above on China's new certification program share two common characteristics. First, they examine the impact of the program by using a dummy indicator that is interpreted as a one-time shock. Therefore, changes over time in the impact of the program are neglected. Second, it remains unclear whether land certification programs lead to changes in welfare inequality in a village in these studies and beyond. A crucial issue for policy making in China is the extent to which the ban on administrative land reallocations within villages and the promotion of market-based land rentals as an alternative land reallocation mechanism have contributed to income inequality within villages. Zhao (2020) finds that the labor-contingent land reallocation administered by village officials in rural China tended to equalize income across households within villages, but at the costs of reduced land tenure security and decreased agricultural productivity. This raises the question whether a tenure-security-enhancing program promoting voluntary land transfers, such as this new certification program, will increase cross-household income inequality.

In this chapter, we empirically investigate the effect of the new land certification program on land rentals, migration, and intra-village income inequality. We use household and village survey data sets collected in early 2019 from six counties in three provinces in China to do the empirical analysis. Our particular interest is in understanding how and to what extent the effects of the program change over time. In this regard, we measure our key explanatory variable as for how many years the program had been completed in a village. Then we correlate this variable to various outcomes. Identifying these estimated effects as causal faces two major empirical challenges. The first challenge is to understand whether the timing of program implementation in villages were correlated with pre-selection household- and/or village-level characteristics. The second challenge is to determine whether other post-certification programs influencing our key outcomes were carried out during the study period. We discuss and address these issues in our econometric analysis.

The main findings in this chapter are three-fold. First, it finds that the relationship between the certification program and households' probability of renting in land has an inverted U-shape: the program significantly increases the probability of renting in land in the first a few years, and then the probability reaches the highest after approximately three years the program was completed, but after five years it drops back to below the probability level as one year after program completion. Meanwhile, there is no statistically significant effect of the program on the probability of renting out land. Second, we find no significant effect of the certification program on household migration. This finding is robust with respect to the choice of migration measures and to a joint estimate of household migration and land rental decisions. Third, there is also no statistically significant effect of the program on intra-village income inequality. Since land certification programs are expected to affect incomes through land and labor reallocations, this result suggests that the income effect of increased land renting-in by farmers is small. However, unlike what has been documented for tenure-security-reducing administrative land reallocations, we find no evidence that this tenure-security-enhancing program contributes to higher within-village income inequality.

Our study directly complements the previously mentioned literature on studying the impact of the same certification program on land and labor reallocation (see Cheng et al., 2016; Wang et al., 2018; Zhang et al., 2019; Gao et al., 2021). While they focus on the one-time shock effects of this program on factor reallocation and aggregate agricultural output, we investigate the effects of the program over time and extend the literature to also include the analysis of intra-village inequality. In a broader sense, these tasks also complement the literature that examines the effect of land tenure security on similar economic outcomes in other contexts. For example, Valsecchi (2014) and de Janvry et al. (2015) study the impact of the 1990s land titling program among Mexican ejidos and find that it increased both international and internal migration of ejidatarios. Do and Iyer (2008) find that household land use rights secured by the 1993 Land Law in Vietnam lead to intra-household land reallocation toward long-term crops and labor reallocation toward nonfarm activities. Giles and Mu (2018) find that insecurity of land property rights in Chinese villages, which exists because village leaders use land reallocation as a strategic device in election campaigns, hinders labor migration out of agriculture. Ma et al. (2016) and Ren et al. (2020b) find that the perceived land tenure security derived from land certificates is positively associated with migration among rural households in China. Chari et al. (2021) and Zhao (2020) study the impact of the 2003 RLCL; the former study finds increased land rentals and improved land allocation efficiencies, while the latter finds increased rural-urban migration and reduced intra-village inequality.

This chapter proceeds as follows. Section 4.2 introduces the background of this new land certification program in China. Section 4.3 describes the data set, while Section 4.4 discusses our empirical strategy in detail. Section 4.5 presents the estimation results, combined with a set of robustness checks. It concludes in Section 4.6.

4.2. Background

In the early 1980s, China's Household Responsibility System granted rural households land use rights for 15 years, while the ownership of land remained with village collectives. The size of the land assigned to households by the village leaders was based on the number of persons and/or laborers in a household (Qu et al., 1995). The security of this land tenure system was further enhanced during the second round of land allocation reform (hereafter, the 1998 land reform), which extended the land contract period of farmers for another 30 years and issued land certificates to households for the first time in history. Nevertheless, village-level administrative land reallocations aiming at accommodating within-village demographic changes over time were observed frequently across the country, regardless of the issuance of land certificates. This phenomenon persists in some regions even with the implementation of the 2003 RLCL, which prohibits such reallocations. Moreover, increasing land expropriations in peri-urban areas has led to a sizable increase of land disputes; however, the information contained in the 1998 land certificate cannot be updated to adequately reflect changes in land rights. It could hardly protect the tenure holders against conflicts because the information platform of land transfers and exchanges is severely insufficient. For a similar reason, when the official land registration system of contracts and certificates is lacking, land use rights cannot be used effectively as a collateral to obtain credit. Such situations may undermine the development of the land rental market and hinder households' incentives to participate in off-farm employment.

Given this background, the new round land certification program (hereafter, the program) has been conducted since 2009 to renew the land certificates of households and to establish a land registration system and information platform (MOA, 2011 & 2015). Specifically, first, the program specifies the size of contracted plots, demarcates the land boundaries, and identifies the location, and issues new certificates containing the updated accurate land information for rural households. Second, it establishes a land registration database that records information on land use rights according to land contracts and certificates of households. The registration system provides a legal basis for the settlement of land conflicts and therefore protects households' land contracting and management rights. Third, based on information from the land registration system, the program establishes a publicly available and electronically managed information platform that covers the issuance of certificates, the transfer of lands, and a record of conflicts of land contracting and management rights.

The program was first tested in eight selected villages in 2009 and then gradually expanded at the township level from 2011 to 2013 in hundreds of selected counties throughout the country. With experience accumulated from these pilot areas, there was a large expansion in 2014 when three provinces (i.e., Shandong, Sichuan, and Anhui) and 27 counties in other provinces participated in the program. Then, in 2015 nine additional provinces and in 2016 ten more provinces fully enrolled in this program. These provinces included Jiangsu and Jiangxi in 2015 and Liaoning in 2016, our study areas in this chapter (see next section). At the end of 2018, the program was officially completed across the country. It is important to note that the timing of full expansion within a province does not necessarily imply that all counties, towns, and villages in that province have also implemented the program at the same time. Instead, some lower-level administrations may already have adopted the program earlier, causing time variation across these units even within the same province. The program rollout provides a classic example of China's gradual experimentation of public policies as described by Rozelle and Swinnen (2004) and Xu (2011). This time variation in program implementation and completion plays a crucial role in our empirical strategy, as described in the following sections.

4.3. DATA

4.3.1. DATA COLLECTION

The main data sets that we use consist of a household-level survey data set and a village-level survey data set. Both data sets come from a field survey conducted in February 2019 in six counties in the provinces Liaoning, Jiangsu, and Jiangxi for a project on farm size enlargement, agricultural production efficiency, and environmental spillovers in rural China. Zhou et al. (2019) described in detail how these counties and provinces were selected for a survey carried out in 2014/15. We set up our 2019 survey in the same six counties as they fit into the purpose of our project and meant considerable costs savings in the pre-survey stage in terms of pilot studies and relationship-building with local officials. In our 2019 survey, however, we resampled towns, villages, and households within counties and used different survey questions because lower-level administrations in the 2014/15 survey did not fit well to our project purpose, and also because the survey questions did not provide sufficient information needed for the project.

In each of the six counties, we randomly selected five towns with a systematic sampling method based on their rankings on an ordered list of average household land endowments in the county. Then four villages were randomly selected in each town using the same approach.[25] In the last step, twelve households were selected from each village via a stratified random sampling method. The three strata we used were households who rented in land, who rented out land, and who had no land rental activities. We effectively interviewed 1,420 household respondents to construct the household data set and 120 village officials to construct the village data set. For households, we collected information on their demographics, employment in agriculture and non-agriculture sectors. We also have information on their agricultural land, as well as their income and consumption in 2018. For villages, we collected general information on village demographics, infrastructures, and land and agricultural production.

4.3.2. Timing of program completion

In our 2019 village survey, we particularly asked village respondents in which year the new land certification program had been completed in their village. Importantly, the competition of the program in our survey and in the perceptions of many local village officials is mainly defined as the completion of processes that include land measurements on site, map-making, publicizing of results in the village, and information registration. However, land certificate issuance can lag for a few years. Under this defining scope, we found that 118 villages out of the entire sample had completed the land certification program by the end of 2018, with the remaining two villages coded with missing values.[26] Table 4.1 summarizes this information by county and province. It shows that seven of the sample villages completed the program in 2014, while most villages completed it in 2015 or later. The timing is highly consistent with the information provided in the official documents. For example, the two sample counties in Liaoning Province (Sujiatun and Donggang) were officially selected for the full implementation of the program in 2015, and therefore the number of villages that reported having completed the program increased substantially in the same year.

[25] Up to this stage, 11 out of 120 villages coincided with the 2014/15 survey.

[26] In one village most agricultural land was expropriated for industrial use and the government decided not to carry out the land certification program. In the other village, the interviewed village head failed to accurately recall the year of program completion; in a phone call two years later, the village head that we interviewed in the field had retired and refused to provide information about the certification program completion year.

Table 4.1. Number of villages in each year that completed the certification program

	Liaoning		Jiangsu		Jiangxi		Total
Year	Sujiatun	Dong-gang	Guanyun	Jinhu	Suichuan	Fengcheng	
2014	0	1	1	2	2	1	7
2015	14	4	4	5	2	2	31
2016	4	2	7	6	4	10	33
2017	1	6	5	5	6	6	29
2018	1	7	3	1	6	0	18
Total	20	20	20	19	20	19	118

Source: Authors' own calculation from the village data set in the 2019 survey.

The most important information presented in Table 4.1 is that there is substantial variation in the timing of program completion within each province and even within each county. The time period ranged from 1 to 5 years, with an average of approximately 3 years. In the following sections, we explore this variation and examine its effect on household land rentals, migration, and intra-village income inequality. Note that, in practice, when a village is selected for implementing the program, the whole process from starting to implement until completing the certification tasks usually takes less than one year.[27] For example, the program implementation guideline issued by Liaoning provincial government in 2015 required the certification program to be started in March of a year, and the results should be made public by the end of the same year. Therefore, the year of program completion and the year of program implementation of a village are used interchangeably in this chapter.

4.4. EMPIRICAL STRATEGIES

4.4.1. LAND RENTAL AND MIGRATION MODELS

Theoretically, land certification programs are expected to influence land rentals and migration through enhanced land tenure security. Secured land tenure rights, on the one hand, may reduce transaction costs in land rental markets and encourage long-term agricultural investments (Besley, 1995; Besley and Ghatak, 2010; Deininger et al., 2011). On the other hand, it may also allow farmers to exit agriculture and participate in (temporary) rural-urban migration while retaining land rights (Deininger et al., 2011; Deininger et al., 2014; de Janvry et al., 2015). To estimate the impact of the certification program on land rental activities and migration, we formulate the following estimating equation:

[27] Again, this usually does not include the task of issuing land certificates.

$$y_{ij} = \alpha_1 Certif\_Years_j + \alpha_2 Certif\_Years_j^2 + \boldsymbol{H_{ij}\phi} + \boldsymbol{V_j\delta} + x_p + \varepsilon_{ij} \qquad (4.1)$$

where y_{ij} denotes one of the four measures of land rental activities and migration for household i in village j (i.e., whether household has land renting-in and land renting-out for measuring land rental activities, and whether household has at least one migrant and household migration ratio for measuring migration; detailed definitions will be discussed in Section 4.5.1). $Certif\_Years_j$ is a discrete variable measuring the number of years the program had been completed in village j; its squared term is included to capture the potentially non-linear effect of the certification program over time. x_p denotes province fixed effects, which are included to capture province-specific factors that may affect household land rentals and migration. ε_{ij} is a random error term with standard properties, and α_1, α_2, $\boldsymbol{\phi}$ and $\boldsymbol{\delta}$ are parameters to be estimated.

The vector $\boldsymbol{H_{ij}}$ is a set of household-level covariates, which include five household demographic measures (household size, number of children, number of elderly, whether there were one or more household members with poor health condition, and household average years of schooling), four household head characteristics (household head age, and whether the household head had any experience in agricultural skills training, in non-agricultural skills training, and of being a village official), and two farm characteristics (per capita contracted land size during the 1998 land reform, and the number of plots of the contracted land during the 1998 land reform). These micro-level covariates are assumed to directly affect household-level decisions on land renting and migration (see for example Cheng et al., 2016; Wang et al., 2018; Zhang et al., 2019; Ren et al., 2020b). For example, larger household size may increase the probability of renting land and migration as the need of more land is higher and more laborers are available to be reallocated to non-agricultural sector. The number of children and the elderly, and the existence of members with poor health conditions, may otherwise discourage migration, since these family members usually have no or limited ability to work and require frequent care from other family members.

The vector $\boldsymbol{V_j}$ consists of three village-level variables serving as proxies of land tenure security of village j: (*i*) whether land certificates had been issued to households following the 1998 land reform, (*ii*) whether administrative land reallocation(s) happened after the 1998 land reform, and (*iii*) whether land expropriation happened before the 2019 survey. These tenure security proxies may affect household decisions on land renting and migration in addition to the tenure security derived from the new land certification program. For instance, administrative land reallocation(s) can also be viewed as an alternative way to adapt land holding sizes to changing household sizes. Hence, they can reduce the need for land rentals.

4.4.2. INTRA-VILLAGE INEQUALITY MODEL

The channels through which land certification programs influence intra-village income inequality can be diverse. More secure land tenure rights derived from land certification programs may encourage agricultural investments, relax credit restrictions, and allow households to allocate land and labor in a more efficient manner. All these channels could translate into household welfare (e.g., income or consumption) and subsequently change the welfare distribution across households (Besley and Ghatak, 2010; de Janvry et al., 2015; Zhao, 2020). However, it largely remains unclear whether this change leads to a larger inequality in welfare in a village. Zhao (2020) has found that the labor-contingent land reallocation administered by village officials in rural China tended to equalize incomes across household within villages.[28] But would a tenure-security-enhancing program that promotes *voluntary* land transfers also reduce household income inequality within villages? If farm households respond differently to the program, e.g., because they differ in their efficiency in agricultural production or in their perceptions of the tenure security that the program provides, then the program will lead to heterogeneous outcomes in terms of farmers' land use and migration decisions (see for example Ma et al., 2015; Ren et al., 2020b). This may translate into different welfare outcomes. To estimate the impact on intra-village welfare inequality, we formulate the village-level equation as

$$y_j = \beta_1 Certif\_Years_j + \beta_2 Certif\_Years_j^2 + \boldsymbol{Z_j}\boldsymbol{\psi} + \boldsymbol{V_j}\boldsymbol{\delta} + x_p + \epsilon_j \tag{4.2}$$

where y_j measures intra-village income inequality in village j. The vector $\boldsymbol{V_j}$ and x_p are defined the same as in equation (4.1). ϵ_j is a random error term, and β_1, β_2, $\boldsymbol{\psi}$ and $\boldsymbol{\delta}$ are parameters to be estimated. $\boldsymbol{Z_j}$ is a vector of village covariates containing five intra-village dispersion measures of household-specific factors, i.e., household dependency ratio, household average years of schooling, household assets, per capita contracted land size during the 1998 land reform, and number of contracted land plots during the 1998 land reform. Many of these variables are aggregates of household covariates in H_{ij}. We expect that intra-village dispersions of these covariates, at least in the short term, will tend to influence the variation in household income either directly or through channels such as land and labor reallocation. The idea of linking inequality measure to dispersions of potential driving factors has been explored, for example, in Kung and Lee (2001) and Foster and Rosenzweig (2003), where the former finds that rising variance in household average education leads to lower intra-village income inequality in China while variance in per capita land size positively affects inequality.

Two additional empirical concerns may challenge the identification of the above models. First, in the household-level analysis of equation (4.1), there might be a simultaneity issue if households that were more likely to rent land or migrate demanded the program more urgently. However, this possibility is ruled out because the program was

[28] This is realized partly because land reallocation leads to efficient cross-household land transfers and hence an improvement in agricultural productivity, and partly because land reallocation functions as a wealth-redistribution and social insurance mechanism, which can also be conveyed from Besley and Burgess (2000).

implemented simultaneously across an entire village, and the timing of program implementation is therefore not likely to be driven by an individual household's demand for land certification. Second, in the village-level analysis of equation (4.2), if villages selected for earlier program implementation significantly differ in their income inequality levels, then estimates of the model can be biased. This possibility has been extensively examined in previous studies focusing on the same program; they have documented that the selection of villages into the program was generally not correlated with pre-selection village characteristics (see Cheng et al., 2016; Wang et al., 2018; Zhang et al., 2019; Gao et al., 2021). We will discuss more about model identification in the following section.

4.5. RESULTS

4.5.1. DESCRIPTIVE STATISTICS

Table 4.2 reports the descriptive statistics of the key variables used to estimate equations (4.1) and (4.2). The upper panel summarizes the dependent variables. Two dummy variables are constructed respectively to measure whether there were land renting-in and land renting-out activities for a household in 2018. It shows that 38% of the 1,396 households reported land renting-in and 33% reported land renting-out.[29] Household migration is measured by two alternative variables: one is a dummy variable indicating whether a household had at least one member migrated in 2018, and the other is a ratio capturing the proportion of household laborers migrated in 2018. In our sample, 48% of households had at least one migrant member, while the average migration ratio across these households was 0.25 in 2018.[30] The intra-village income inequality, which is measured by Gini index of per capita household income,[31] was 0.51 with a standard deviation of 0.13. The lowest intra-village inequality level was 0.20, while the highest was 0.89 in 2018. Interestingly, villages falling into the lowest 5 percentiles of the inequality distribution were mostly from Jiangsu Province, while those in the highest 5 percentiles were mainly in Liaoning and Jiangxi.

[29] We drop the 24 households in the two villages where land certification information is missing (see Section 4.3). This leaves us a sample size of 1,396 out of 1,420 households.

[30] Migration ratio is defined as the ratio of the number of migrants to the total number of laborers in a household. A laborer is a household member who ages between 16 and 65 and has a non-poor health condition (i.e., >1 in our five-degree measure of heath condition), and a migrant is defined as a laborer who worked off-farm for at least six months in 2018 and did not stay at home in the village during the off-farm work.

[31] To compute the Gini index of intra-village income inequality for n households living in village j, we use

$$Gini_j = \frac{1}{2n^2\overline{x_j}} \sum_{i=1}^{n} \sum_{m=1}^{n} |x_{ij} - x_{mj}|$$

where $i, m = 1,2, \dots, n$ denote households. x_{ij} denotes per capita household income aggregated from agricultural production, wages, family businesses, house and land rents, pensions, subsidies, etc., and $\overline{x_j}$ is the average per capita household income in village j.

Table 4.2. Descriptive statistics of the key variables used in equations (4.1) and (4.2)

Variables	Obs.	Unit	Mean	Std. Dev.	Min	Max
Dependent variables						
Household rented in land	1,396	Yes=1	0.38	0.49	0	1
Household rented out land	1,396	Yes=1	0.33	0.47	0	1
Household had one or more migrants	1,396	Yes=1	0.48	0.50	0	1
Household migration ratio	1,396		0.25	0.31	0	1
Intra-village income inequality	118		0.51	0.13	0.20	0.89
Explanatory variables						
Years after program completion	118	Years	2.83	1.16	1	5
Household demographic measures						
Household size	1,396		3.95	1.91	1	14
Number of children	1,396		0.59	0.92	0	6
Number of elderly	1,396		0.65	0.83	0	3
Has members with poor health condition	1,396	Yes=1	0.15	0.35	0	1
Household average schooling years	1,396	Years	6.57	2.58	0	15
Household head characteristics						
Household head age	1,396	Years	59.71	9.66	27	89
Training in agricultural skills	1,396	Yes=1	0.34	0.47	0	1
Training in non-agricultural skills	1,396	Yes=1	0.13	0.34	0	1
Experience of being a village official	1,396	Yes=1	0.17	0.38	0	1
Farm characteristics						
Per capita contracted land size in 1998 land reform	1,396	Mu	2.64	2.77	0	37.5
Number of land plots in 1998 land reform	1,396		4.18	4.51	0	92
Village-level tenure security proxies						
Land certificates issued after 1998	118	Yes=1	0.77	0.42	0	1
Land reallocation happened after 1998	118	Yes=1	0.47	0.50	0	1
Land expropriation happened before 2019	118	Yes=1	0.44	0.50	0	1
Within-village dispersions						
CV of household dependency ratio	118		1.15	0.37	0.48	2.16
CV of household average schooling years	118		0.36	0.13	0.14	0.73
CV of household asset value by the end of 2017	118		1.15	0.47	0.44	2.92
CV of per capita contracted land size in the 1998 land reform	118		0.79	0.34	0.33	2.52
CV of number of contracted land plots in the 1998 land reform	118		0.60	0.24	0	1.32

Data source: Authors' own calculation from the 2019 household and village survey data sets.

Notes: CV in variable names denotes the coefficient of variation.

The lower panel of Table 4.2 summarizes the key explanatory variables. On average, the sample villages had completed the certification program for approximately 3 years, in a range of 1 to 5 years. The mean household size was approximately 4, with less than 1 child and 1 elderly on average in each household; a "child" is defined as a person who is under 16 years old, and an "elderly" is defined as a person who is above 65 years old. 15% of the households had one or more members with poor health conditions, which the respondent self-evaluated based on five degrees (from poor to very good) during our 2019 field survey. The sample average of household mean schooling years was approximately 6.6 years in 2018, with some households having no educated members. The average age of household heads in the sample was approximately 60 years old, with 34% of them previously participated in agricultural skills training, 13% of them participated in non-agricultural skills training, and 17% had experience being village officials. The per capita land size, which is calculated as the ratio of contracted land size during the 1998 land reform to the present-day household size in the 2019 survey, was about 2.6 mu (1 mu=1/15 ha) on average, and the contracted land plots on average was 4.2. Both per capita land size and land plots vary significantly across the sample households.

For village-level proxy measures of land tenure security, 77% of sample villages issued the old land certificate following the 1998 land reform, 47% of them reallocated land at least once after the 1998 land reform, and 44% had experienced land expropriation. The household dependency ratio measures the ratio of the sum of children, elderly and members of poor health conditions to the total number of household laborers. The average within-village coefficient of variation of this variable was 1.15 in 2018. Household asset value was measured up to the end of 2017, which included self-reported market values of agricultural machinery, houses, transportation vehicle, livestock, forestry, household appliances, etc. It had an average coefficient of variation of 1.15 across villages.

4.5.2. IMPACT ON LAND RENTAL DECISIONS

Table 4.3 reports the parameter estimates of equation (4.1) from probit regressions. In all estimations, we cluster standard errors at the village level because of concerns about the potential within-village correlation of the residuals that may particularly arise from our cluster-stratification sampling of households (see Abadie et al., 2017). In columns (1)-(3), the dependent variable is whether a household had rented in agricultural land in 2018. We start with regressing this dependent variable on the years after program completion, its quadratic terms, and province fixed effects in column (1), and then augment the model to also include household-level covariates in column (2), and in the last we add on village-level tenure security proxies in column (3), which constitutes our main model as specified in equation (4.1). All three regressions show that the relationship between the years after program completion and household land renting-in is robustly concave and statistically significant, either with or without additional covariates being controlled for. The renting-

Table 4.3. Regression results for household land rental decisions, probit model

	Dependent variable: Household rented in land			Dependent variable: Household rented out land		
	(1)	(2)	(3)	(4)	(5)	(6)
Years after program completion	0.264**	0.263**	0.280**	-0.022	0.025	0.061
	(0.11)	(0.13)	(0.14)	(0.11)	(0.12)	(0.14)
Years after program completion × Years after program completion	-0.044**	-0.045**	-0.049**	0.007	-0.000	-0.007
	(0.019)	(0.023)	(0.024)	(0.022)	(0.022)	(0.025)
Household demographic measures						
Household size		0.085**	0.083**		-0.163***	-0.164***
		(0.037)	(0.037)		(0.037)	(0.037)
Number of children		0.026	0.029		0.042	0.042
		(0.069)	(0.070)		(0.078)	(0.079)
Number of elderly		-0.108*	-0.107*		0.108*	0.109*
		(0.058)	(0.059)		(0.060)	(0.060)
Has members with poor health condition		-0.074	-0.061		0.011	0.017
		(0.10)	(0.10)		(0.098)	(0.096)
Household average schooling years		-0.001	-0.002		0.002	0.001
		(0.019)	(0.019)		(0.018)	(0.018)
Household head characteristics						
Household head age		-0.027***	-0.027***		0.016***	0.016***
		(0.0048)	(0.0048)		(0.0051)	(0.0051)
Training in agricultural skills		0.542***	0.543***		-0.315***	-0.314***
		(0.084)	(0.084)		(0.081)	(0.081)
Training in non-agricultural skills		-0.186*	-0.186*		0.221**	0.222**
		(0.11)	(0.11)		(0.11)	(0.11)
Experience of being a village official		-0.256***	-0.254***		0.115	0.117
		(0.097)	(0.097)		(0.098)	(0.098)

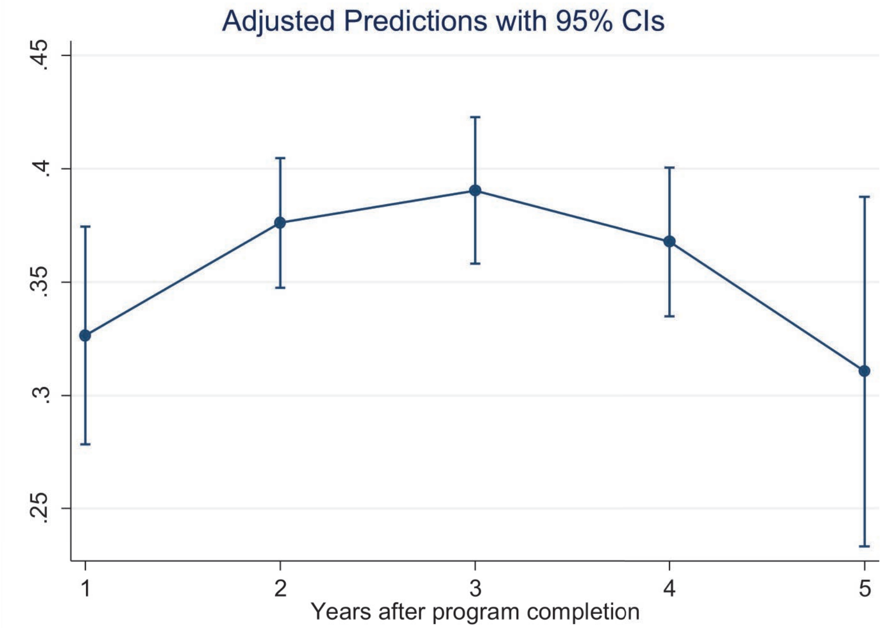
Farm characteristics						
Per capita contracted land size in 1998 land reform		0.007	0.006		-0.031**	-0.032**
		(0.016)	(0.016)		(0.015)	(0.015)
Number of land plots in 1998 land reform		-0.010	-0.011		0.010	0.009
		(0.0078)	(0.0078)		(0.0078)	(0.0079)
Village-level tenure security proxies						
Land certificates issued after 1998			-0.069			-0.012
			(0.089)			(0.076)
Land reallocation happened after 1998			0.047			0.026
			(0.059)			(0.058)
Land expropriation happened before 2019			0.066			0.071
			(0.065)			(0.078)
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.726***	0.520	0.518	-0.360***	-0.798**	-0.870**
	(0.14)	(0.40)	(0.40)	(0.13)	(0.37)	(0.39)
N	1,396	1,396	1,396	1,396	1,396	1,396
Pseudo R^2	0.004	0.087	0.088	0.003	0.059	0.060
Wald χ^2	13.308	163.017	182.348	8.545	99.801	100.971
	[0.010]	[0.000]	[0.000]	[0.074]	[0.000]	[0.000]

Notes: Estimations are clustered in 118 villages. Parameter estimates are reported, with clustered robust standard errors in parentheses. p-values of Wald χ^2 are in square brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

in probability first increases with the number of post-program years; it reaches the turning point after approximately three years (0.28/(2*0.049)), and then declines thereafter.

This non-linear relationship is more clearly seen through Figure 4.1, which plots the predicted probabilities of renting in land over time according to the estimates in column (3). The figure exhibits a clear inverted U-shape, with the turning point plotted in the third year (around the mean of the variable $Certif\_Years$) after the program has been completed. The increasing part of the curve suggests that perceptions of tenure security may take time to develop in the years after the program was implemented. This is consistent with the argument of Cheng et al. (2016) that agricultural land may still risk administrative reallocation within villages and, therefore, farmers may need time to build up trust toward this new certification program.

Figure 4.1. Impact of post-certification time on household's land renting-in decision



Notes: The figure plots the predicted probabilities of renting in land over the years after program completion, while holding other explanatory variables at their means. Pointwise 95% confidence intervals for the fitted values are included.

The inverted U-shaped curve starts to decline after approximately three years of program completion, which seems to indicate that tenure security perceptions derived from the certification program decline after a few years. We argue that this can be true if farmers in the subsequent years observe any practices that potentially downplay the importance of the certification program. One such example might be that, in our 2019 village survey, none of the 40 sample villages in Liaoning Province had issued the land certificates associated with this new certification program, though approximately half of them had completed other certification tasks (e.g., land measurement, map-making, results publicizing and information registration) as early as in 2015 (i.e., for four years; see Table 4.1); seven villages in Jiangsu and Jiangxi are observed with situations similar to that of Liaoning. On the other hand, the observed decline in the probability of land renting-in after a few years of program implementation may also reflect changes over time in the village-level supply of agricultural land (i.e., land renting-out households) after the implementation of the program. We explore this in the following.

While columns (1)-(3) find a significant non-linear effect of the program on land renting-in activities, we do not find a similar impact that is statistically significant on land renting-out activities in columns (4)-(6). Such findings do not justify our previous argument that village-level supply of agricultural land declines over time. They differ from Cheng et al. (2016) and Wang et al. (2018) but are consistent with Zhang et al. (2019). The latter study finds that the impact of the new land certification program on land renting-in is significantly positive while its impact on land renting-out is statistically insignificant. The findings by Zhang et al. (2019) and our study suggest that land renting-in and renting-out within the same village is affected by different factors, with the new land certification program only affecting renting-in decisions. Land renting-in households may pay more attention to the program as they tend to rely more on agriculture for a living, while land renting-out households tend to focus more on non-agricultural job and may therefore attach less value to a program enhancing the tenure security of agricultural land.

As regards the parameter estimates of household and village control factors, a general finding by looking at columns (3) and (6) in Table 4.3, our preferred estimating models as specified in equation (4.1), is that these factors influence land renting-in and renting out in opposite directions. This is consistent to a large extent with our discussions in Section 4.1. In particular, we find that household size and household head training experience in agricultural skills significantly increase the probability of renting in land and negatively affect land renting-out probability. The number of elderly in a household, and the household head's age and training experience in non-agricultural skills, significantly decrease land renting-in probability while increasing the probability of land renting-out. A household head's experience of being a village official significantly reduces the probability of renting in land, but its impact on land renting-out is estimated as insignificant. The per capita contracted land size negatively affects the probability of renting out land, while its estimated impact on land renting-in is insignificant. These findings, either about land renting-in decisions or about land renting-out decisions, are in general consistent with findings in Ma et al. (2020), Cheng et al. (2016), and Wang et al. (2018).

4.5.3. IMPACT ON MIGRATION

To test the impact of the program on migration, we use two different measures of migration to estimate equation (4.1). Similar to Section 4.5.2, all regressions cluster the standard errors at the village level. In columns (1)-(3) of Table 4.4, the dependent variable is a dummy indicating whether a household had at least one migrant member in 2018. We therefore report the parameter estimates from probit regressions in these columns. In general, we do not find evidence that the new land certification program has a statistically significant impact on migration. Previous research found a significant positive impact of land tenure security generated from the restriction of land reallocations and the 1998 land certificates on migration (e.g., Zhao, 2020). Our result suggests that the new round of land certification does not further promote migration, even after several years.

Nevertheless, in column (3), we find that larger household size and more average schooling years of household members increase the probability of having one or more migrants in the household. All other household demographic measures (i.e., number of children, number of the elderly, and whether they have members with poor health condition) significantly decrease the probability of migration. Although the training experience of the household head in non-agricultural skills does not significantly increase the probability of having one or more migrants in a household, the training experience in agricultural skills is found to significantly discourage migration. The contracted land size per capita has a similar effect; households with larger contracted land size per capita are less likely to become migrant households. Village-level tenure security proxies are all estimated as insignificant in column (3). This is different from the study of, for instance, Deininger et al. (2014), who find that secured tenure rights encourage rural-urban migration, though they do not study the effect over time.

One potential problem of using a dummy variable to measure household migration is that it fails to reflect the program effect if the program mainly encourages more household members in an incumbent migrant household to migrate. To address this concern, we use migration ratio as an alternative measure to estimate equation (4.1). The OLS estimation results are reported in columns (4)-(6) of Table 4.4. All regressions show that the relationship between the years after program completion and household migration ratio is statistically insignificant. For household and village covariates, those that have been found significantly determine whether a household has at least one migrant member in column (3) are mostly confirmed in column (6): the signs and significance levels of these previously estimated effects are generally preserved with only a few exceptions. Specifically, there is no statistically significant evidence that the number of elderly, or whether there were members in a household in poor health condition, influence household migration ratio, while village-level land expropriation experience significantly decreases the migration ratio. A possible explanation for the latter is that land expropriations have forced entire households to migrate out of the village.

Table 4.4. Regression results for household migration

	Probit			OLS		
Dependent variable:	**One or more migrants in household**			**Migration ratio**		
	(1)	(2)	(3)	(4)	(5)	(6)
Years after program completion	0.115	0.071	0.092	0.039	0.036	0.019
	(0.16)	(0.14)	(0.15)	(0.042)	(0.034)	(0.034)
Years after program completion × Years after program completion	-0.016	-0.006	-0.008	-0.005	-0.005	-0.002
	(0.030)	(0.025)	(0.026)	(0.0080)	(0.0065)	(0.0063)
Household demographic measures						
Household size		0.606***	0.612***		0.078***	0.078***
		(0.053)	(0.053)		(0.0071)	(0.0072)
Number of children		-0.588***	-0.597***		-0.064***	-0.063***
		(0.096)	(0.096)		(0.014)	(0.014)
Number of the elderly		-0.410***	-0.417***		-0.019	-0.020
		(0.072)	(0.072)		(0.012)	(0.012)
Has members with poor health condition		-0.372***	-0.391***		-0.035	-0.039
		(0.12)	(0.12)		(0.026)	(0.026)
Household average schooling years		0.057***	0.058***		0.013***	0.013***
		(0.021)	(0.021)		(0.0035)	(0.0035)
Household head characteristics						
Household head age		0.005	0.005		0.001	0.002
		(0.0054)	(0.0053)		(0.0011)	(0.0011)
Training in agricultural skills		-0.153*	-0.155*		-0.052***	-0.053***
		(0.085)	(0.084)		(0.014)	(0.014)
Training in non-agricultural skills		0.064	0.065		0.022	0.021
		(0.13)	(0.13)		(0.023)	(0.023)
Experience of being a village official		-0.010	-0.012		-0.015	-0.016
		(0.11)	(0.11)		(0.020)	(0.020)

Farm characteristics						
Per capita contracted land size in 1998 land reform		-0.047**	-0.045**		-0.009***	-0.009***
		(0.019)	(0.019)		(0.0022)	(0.0022)
Number of land plots in 1998 land reform		0.014	0.014		0.003*	0.003*
		(0.010)	(0.010)		(0.0015)	(0.0015)
Village-level tenure security proxies						
Land certificates issued after 1998			0.151			0.005
			(0.11)			(0.018)
Land reallocation happened after 1998			-0.103			-0.017
			(0.081)			(0.015)
Land expropriation happened before 2019			-0.061			-0.037**
			(0.087)			(0.016)
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.686***	-2.850***	-2.977***	0.084*	-0.276***	-0.238***
	(0.19)	(0.48)	(0.49)	(0.047)	(0.080)	(0.083)
N	1,396	1,396	1,396	1,396	1,396	1,396
R^2				0.083	0.256	0.260
Pseudo R^2	0.062	0.302	0.304			
Wald χ^2	117.244	411.106	416.785			
	[0.000]	[0.000]	[0.000]			
F-value				30.307	44.351	41.686
				[0.000]	[0.000]	[0.000]

Notes: Estimations are clustered in 118 villages. Parameter estimates are reported, with clustered robust standard errors in parentheses. p-values of Wald χ^2 and F-value are in square brackets. * p<0.10, ** p<0.05, *** p<0.01.

Despite these findings, it may still be argued that households' decisions to rent in or rent out land are simultaneously determined with migration decisions (see for example Feng et al., 2010). We therefore also estimate two bivariate probit models: one jointly estimates the land renting-in decision and the binary migration measure, and the other jointly estimates the land renting-out decision and the binary migration. The estimation results are presented in Table A.4.1 of the Appendix. Although the estimated ancillary parameter ρ, which is statistically significantly different from 0, indicates potential correlation of the residuals from the two models in each set of the bi-probit regressions, the main findings are consistent with the previous findings based on treating land rental and migration decisions separately.

4.5.4. IMPACT ON INTRA-VILLAGE INCOME INEQUALITY

Table 4.5 reports the estimates of equation (4.2) at the village level. Columns (1)-(3) show that, with or without controlling for village-level covariates, there is no statistically significant evidence that the land certification program affects intra-village income inequality. This may be expected by noting that the results presented in Sections 4.5.2 and 4.5.3 indicate that the program significantly influences land renting-in, but not land renting-out or migration. Therefore, the overall impact on land and labor reallocation appears to be small and may explain why the impact of the program on household income inequality is not significant. Another possible explanation is that the income measure that makes up our dependent variable may not capture the effect of the certification program because the most important channels that we have distinguished in Section 4.2 affect particularly agricultural incomes. To test this, we measure the intra-village inequality in agricultural income and regress it on the same set of variables. The results are presented in Table A.4.2 in the Appendix. Again, we find no statistically significant evidence that the certification program affects intra-village inequality of agricultural income.

Not surprisingly, we do find in Table 4.5 that variation in cross-household assets in the previous year significantly and positively influences income inequality. However, larger within-village variation in land fragmentation seems to reduce income inequality. One potential reason for this is that households with more fragmented land often have lower agricultural productivity and hence lower agricultural income, but they are also more likely to send more family members to migrate and earn non-agricultural income (our estimation results in columns (5) and (6) in Table 4.4 confirm this). This process facilitates the reduction of within-village income inequality. Interestingly, although we do not find evidence that the new land certification program influences income inequality, the estimation results in Table 4.5 for village-level administrative land reallocation indicates that it significantly reduces intra-village income inequality by approximately 13%. This is highly consistent with the study of Zhao (2020), who finds that administrative land reallocation before the 2003 RLCL significantly reduced cross-household per capita net income inequality.

Table 4.5. OLS regression results for intra-village income inequality

Dependent variable: Log intra-village income inequality (Gini index)	(1)	(2)	(3)
Years after program completion	0.018	-0.019	0.005
	(0.099)	(0.099)	(0.11)
Years after program completion × Years after program completion	0.003	0.010	0.006
	(0.017)	(0.016)	(0.018)
Within-village dispersions			
CV of household dependency ratio		0.040	0.026
		(0.072)	(0.074)
CV of household average schooling years		-0.055	-0.042
		(0.23)	(0.23)
CV of household asset value by the end of 2017		0.163***	0.142***
		(0.054)	(0.050)
CV of per capita contracted land size in the 1998 land reform		0.031	0.069
		(0.10)	(0.100)
CV of number of contracted land plots in the 1998 land reform		-0.146	-0.207*
		(0.11)	(0.11)
Village-level tenure security proxies			
Land certificates issued after 1998			0.045
			(0.065)
Land reallocation happened after 1998			-0.130**
			(0.051)
Land expropriation happened before 2019			-0.052
			(0.053)
Provincial fixed effects	Yes	Yes	Yes
Constant	-0.748***	-0.904***	-0.818***
	(0.14)	(0.17)	(0.19)
N	118	118	118
R^2	0.049	0.137	0.201
F-value	1.464	2.493	2.330
	[0.218]	[0.013]	[0.011]

Notes: OLS estimation results are reported. Robust standard errors are in parentheses, and p-values of F-value are in square brackets. * p<0.10, ** p<0.05, *** p<0.01.

Although we find no statistically significant evidence that the program influences the distribution of household income within villages, one may wonder if it affects the level of household income. After all, growth in income, if any, does not always translate into increased inequality. The welfare impact of land reforms has been studied, for instance, in Zhao (2020), who finds that administrative land reallocation significantly decreases per capital household net income in China, and in de Janvry et al. (2015), who find that land titling program among Mexican ejidos only moderately increased household consumption per capita. Here, we regress the log of household income on the years after program completion, its quadratic terms, and other household and village covariates. For the latter, we particularly use the sets of controlling variables in equation (4.1) plus two additional controls, i.e., the log of household asset value by the end of 2017 and whether household borrowed any money in 2018, to capture respectively the potential effects of initial wealth and loans on household income. The estimation results are reported in Table A.4.3. However, they show that the certification program does not appear to have a statistically significant impact on income, regardless of the channels through which the influence comes.

4.5.5. ADDITIONAL ROBUSTNESS CHECK: IMPACTS OF OTHER PROGRAMS

In the previous subsections, we have found that the land certification program has a significant and inverted U-shaped impact on household's probability of renting in land. We find no statistically significant evidence that the program also influences household's decisions on land renting-out and migration or intra-village income inequality. These findings are robust to various types of alternative estimations. Although we argue that these estimates are not likely to be biased by simultaneity at the household level or by village selection into the program at the village level, our estimates may still be biased if other programs driving the outcomes were implemented in villages selected later for the certification program. In our study period, i.e., from 2014 to 2018, one such potential program is the relaxation of using contracted and/or rented agricultural land as collateral for borrowing. Specifically, in late 2015, the National People's Congress (the central legislature of China) temporarily revoked relevant articles in China's Property Law and Guarantee Law and legislated to allow farming entities in 232 pilot counties to use the land management rights as a collateral to borrow from financial intermediaries. Since collateralized borrowing purposes are limited to agricultural production, we expect this legal reform to directly affect household land rental activities, while indirectly affecting migration and income levels.

In our data set, 39 villages in two counties (Donggang in Liaoning Province and Jinhu in Jiangsu Province) were part of this pilot legislative reform, while the other four counties were not. To capture potential impact of this legal reform, we construct a dummy variable that takes the value of 1 for villages implemented the reform and 0 for other villages, and we re-estimate equations (4.1) and (4.2) by controlling for this additional variable. The results are presented in Table A.4.4 in the Appendix. The main message from these regressions is that the inclusion of the legal reform term does not significantly change our key findings from previous estimates. Nonetheless, the legal reform itself is found to significantly increase the probability of renting out land, while shows no significant effect on land renting-in probability. One possible explanation for this is that the legal reform may have motivated the expansion or entry of some large family farms or agribusiness firms, and their participation has induced a non-trivial proportion of households in our sample to rent out land. We leave this for future studies where such data is available.

4.6. CONCLUSION

In this chapter, we have examined the impact of the recent land certification program on rural households' land rental decisions, migration, as well as intra-village income inequality, using survey data collected in three provinces in China. The empirical results show that the land certification program influences households' land renting-in decisions nonlinearly over time: it increases households' probability of renting in land, but after approximately three years, the predicted probability starts to decline. Significant evidence has not been detected for households' decisions on land renting-out and migration decisions. Likewise, the land certification program does not contribute to the intra-village income inequality.

These findings have several important implications for public policy. First, they renew our understanding of farm size enlargement policies in China. In particular, they imply that the land certification program would encourage lessee's land renting-in activities, while does not improve potential landlords' incentives to rent out land. To some extent, this finding might explain the slow growth of large-scale agriculture in recent years in China. Additional policies that promote land leases and balance the demand and supply of land would be important for the further development of the land lease market and large-scale farming in rural China. Moreover, as the impact on land renting-in declines in a few years, policies toward continuous reinforcement of land tenure security may be needed to facilitate land consolidation in the long run.

Second, the new round of the land certification program does not encourage migration as previous policies have done to improve land tenure security. In contrast, education seems to continue to play an important role in stimulating migration, and therefore policies that support the accumulation of human capital would have a more significant impact on the occupational choice of rural households than policies that improve the security of land tenure. Meanwhile, household demographics such as children, elderly, and health issues significantly hinder migration, and addressing these issues alternatively requires improved social securities and health care insurance.

Third, in our study, the land certification program is expected to affect household income primarily through land and labor reallocations. Influences from other channels, such as borrowing for agricultural investment, can be limited, since more than half of the sample households were restricted from collateralizing their land management rights. In this regard, our estimate suggests that the income effect of increased land renting-in by farmers is trivial, such that the overall effects of the land certification program on household income (see Table A.4.3) and income inequality (see Table 4.4) have not been significantly detected. Yet, unlike administrative land reallocations, for which Zhao (2020) has found reducing cross-household income inequality with non-trivial costs of declined land tenure security and aggregate agricultural productivity, our study finds that the tenure-security-enhancing program does not seem to contribute to larger within-village income inequality.

Our study bears several limitations, and we particularly discuss two that we think might be important for this and future studies. First, in our empirical analysis, we strive to reduce the potential confounding effects of observables. However, unobserved factors may still lead to biased estimates. It is impossible to directly estimate the causal impact in the absence of panel data containing pre- and post-certification data. Therefore, the robustness of our study should be further tested using panel data sets in future studies. Second, this study exploits the variation of the certification program at the village level; however, as we have stressed for several times in previous discussions, it might be farmers' perceived tenure security, i.e., the perceived variation of the program at the household level, that matters for factor reallocation. This is surely worthy of future studies.

APPENDIX

Table A.4.1. Bivariate probit regression results for land rentals and migration

	bi-probit regression		**bi-probit regression**	
	(1)	(2)	(3)	(4)
Dependent variable	Household rented in land	Household had one or more migrants	Household rented out land	Household had one or more migrants
Years after program completion	0.279**	0.094	0.058	0.097
	(0.14)	(0.15)	(0.14)	(0.15)
Years after program completion × Years after program completion	-0.048**	-0.008	-0.006	-0.009
	(0.025)	(0.026)	(0.025)	(0.027)
Household demographic measures				
Household size	0.082**	0.615***	-0.164***	0.611***
	(0.036)	(0.054)	(0.037)	(0.053)
Number of children	0.029	-0.602***	0.043	-0.595***
	(0.070)	(0.097)	(0.079)	(0.097)
Number of elderly	-0.105*	-0.418***	0.107*	-0.417***
	(0.059)	(0.073)	(0.060)	(0.072)
Has members with poor health condition	-0.064	-0.390***	0.017	-0.386***
	(0.10)	(0.12)	(0.096)	(0.12)
Household average schooling years	-0.002	0.057***	0.001	0.059***
	(0.018)	(0.020)	(0.018)	(0.020)
Household head characteristics				
Household head age	-0.027***	0.006	0.016***	0.006
	(0.0048)	(0.0054)	(0.0051)	(0.0053)
Training in agricultural skills	0.544***	-0.155*	-0.313***	-0.155*
	(0.085)	(0.085)	(0.081)	(0.084)
Training in non-agricultural skills	-0.186*	0.066	0.222**	0.060

	(0.11)	(0.13)	(0.11)	(0.13)
Experience of being a village official	-0.256***	-0.009	0.115	-0.007
	(0.098)	(0.11)	(0.098)	(0.11)
Farm characteristics				
Per capita contracted land size in 1998	0.006	-0.044**	-0.031**	-0.044**
land reform	(0.016)	(0.019)	(0.015)	(0.019)
Number of land plots in 1998 land reform	-0.011	0.014	0.009	0.014
	(0.0077)	(0.0098)	(0.0079)	(0.010)
Village-level tenure security proxies				
Land certificates issued after 1998	-0.070	0.154	-0.009	0.147
	(0.089)	(0.11)	(0.076)	(0.11)
Land reallocation happened after 1998	0.047	-0.106	0.027	-0.103
	(0.059)	(0.080)	(0.058)	(0.081)
Land expropriation happened before 2019	0.067	-0.063	0.071	-0.062
	(0.065)	(0.086)	(0.078)	(0.088)
Provincial fixed effects	Yes	Yes	Yes	Yes
Constant	0.519	-2.997***	-0.885**	-2.999***
	(0.40)	(0.49)	(0.39)	(0.49)
N	1,396		1,396	
Wald test of $\rho = 0$: $\chi^2(1)$ (Prob>χ^2)	10.526		5.941	
	(0.0012)		(0.015)	
Log pseudolikelihood	-1511.338		-1503.565	
Wald χ^2	771.421		622.134	

Notes: All estimations are clustered in 118 villages. For the Wald-tests, p-values are reported in parentheses. Parameter estimates are reported for explanatory variables in all columns. Cluster-robust standard errors are in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table A.4.2. OLS regression results for intra-village inequality of agricultural income

Dependent variable: **Log intra-village agricultural income inequality (Gini index)**	(1)	(2)	(3)
Years after program completion	-0.012	-0.013	0.061
	(0.14)	(0.13)	(0.14)
Years after program completion × Years after program completion	0.005	0.007	-0.006
	(0.025)	(0.024)	(0.026)
Within-village dispersions			
CV of household dependency ratio		-0.021	-0.023
		(0.11)	(0.11)
CV of household average schooling years		0.030	0.094
		(0.31)	(0.31)
CV of household asset value by the end of 2017		0.100	0.103
		(0.065)	(0.062)
CV of per capita contracted land size in the 1998 land reform		-0.180	-0.181
		(0.13)	(0.13)
CV of number of contracted land plots in the 1998 land reform		-0.125	-0.144
		(0.15)	(0.15)
Village-level tenure security proxies			
Land certificates issued after 1998			0.012
			(0.073)
Land reallocation happened after 1998			-0.012
			(0.060)
Land expropriation happened before 2019			0.104
			(0.069)
Provincial fixed effects	Yes	Yes	Yes
Constant	-0.561***	-0.516**	-0.681**
	(0.17)	(0.25)	(0.30)
N	118	118	118
R^2	0.108	0.169	0.190
F-value	3.673	2.266	2.342
	0.008	0.023	0.011

Notes: OLS estimation results are reported. Robust standard errors are in parentheses, and p-values of F-value are in square brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4.3. OLS regression of the effect of land certification program on household income

Dependent variable: **Log (annual income per household member in 2018)**	(1)	(2)	(3)
Years after program completion	0.176	0.118	0.216
	(0.19)	(0.17)	(0.16)
Years after program completion × Years after program completion	-0.025	-0.017	-0.039
	(0.033)	(0.029)	(0.029)
Household demographic measures			
Household size		-0.045	-0.094***
		(0.030)	(0.027)
Number of children		-0.061	-0.043
		(0.062)	(0.060)
Number of elderly		-0.029	-0.030
		(0.044)	(0.041)
Has members with poor health condition		-0.396***	-0.261***
		(0.099)	(0.097)
Household average schooling years		0.076***	0.056***
		(0.017)	(0.017)
Household head characteristics			
Household head age		-0.023***	-0.018***
		(0.0042)	(0.0040)
Training in agricultural skills		0.394***	0.329***
		(0.082)	(0.081)
Training in non-agricultural skills		0.278**	0.253**
		(0.11)	(0.11)
Experience of being a village official		0.103	0.076
		(0.084)	(0.082)
Farm characteristics			

Per capita contracted land size in 1998 land reform		0.024**	0.022**
		(0.0100)	(0.0097)
Number of land plots in 1998 land reform		0.002	0.002
		(0.0082)	(0.0077)
Village-level tenure security proxies			
Land certificates issued after 1998			-0.125
			(0.086)
Land reallocation happened after 1998			0.008
			(0.068)
Land expropriation happened before 2019			0.154**
			(0.074)
Log of household asset value in 2017			0.271***
			(0.029)
Household had borrowing experience in 2018			0.019
			(0.11)
Provincial fixed effects	Yes	Yes	Yes
Constant	9.253***	10.092***	9.303***
	(0.25)	(0.35)	(0.35)
N	1,377	1,377	1,377
R^2	0.080	0.225	0.289
F-value	18.390	25.130	29.502
	[0.000]	[0.000]	[0.000]

Notes: All columns perform OLS regression by clustering the standard errors in the village. Cluster-robust standard errors are in parentheses; p-values for F-value are in square brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4.4. The impact of land certification program by controlling for the effect of legal reform

Dependent variable	(1) Household rented in land (Probit)	(2) Household rented out land (Probit)	(3) Household had one or more migrants (Probit)	(4) Household migration ratio (OLS)	(4) Log of Intra-village income inequality (OLS)
Years after program completion	0.284**	0.077	0.074	0.015	-0.001
	(0.14)	(0.14)	(0.15)	(0.034)	(0.11)
Years after program completion × Years after program completion	-0.049**	-0.008	-0.007	-0.001	0.006
	(0.024)	(0.025)	(0.026)	(0.0062)	(0.018)
Experienced legal reform in late 2015	0.056	0.161**	-0.189**	-0.035*	-0.091
	(0.064)	(0.073)	(0.088)	(0.018)	(0.062)
Control:					
Household demographic measures	Yes	Yes	Yes	Yes	
Household head characteristics	Yes	Yes	Yes	Yes	
Farm characteristics	Yes	Yes	Yes	Yes	
Village-level tenure security proxies	Yes	Yes	Yes	Yes	Yes
Within-village dispersions					Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	0.474	-0.999**	-2.832***	-0.209**	-0.715***
	(0.40)	(0.40)	(0.49)	(0.086)	(0.19)
N	1,396	1,396	1,396	1,396	118
R^2				0.262	0.216
Pseudo R^2	0.088	0.061	0.306		
Wald χ^2	180.765	122.203	418.595		
	[0.000]	[0.000]	[0.000]		
F-value				39.480	2.125
				[0.000]	[0.018]

Notes: Columns (1)-(4) cluster the estimation in 118 villages. Cluster-robust standard errors are in parentheses in columns (1)-(4); robust standard errors are in parentheses in column (5); p-values for Wald χ^2 and F-value are in square brackets. * p<0.10, ** p<0.05, *** p<0.01.

CHAPTER 5
FERTILIZER USE IN A CREDENCE GOOD MARKET: EVIDENCE FROM CHINESE RICE FARMERS*

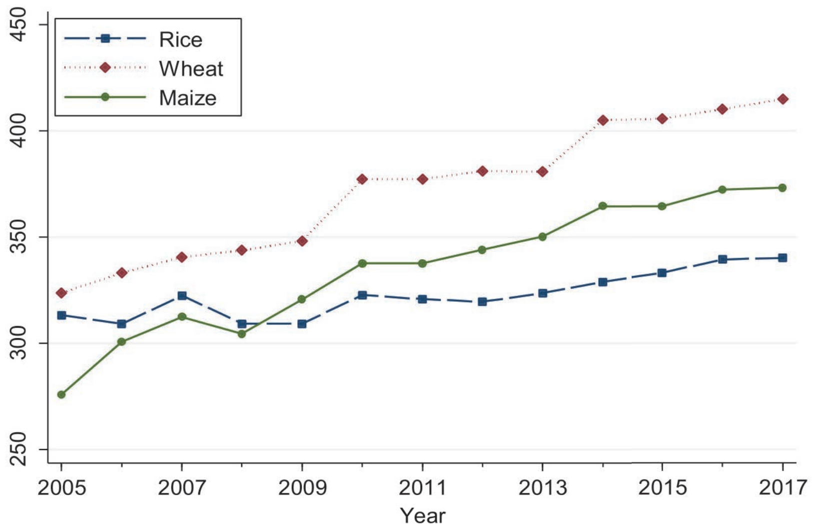
ABSTRACT This chapter examines whether the high intensity of chemical fertilizer use by Chinese farmers is related to the sources that provide information about fertilizer use, with a particular focus on the role of fertilizer sellers. We argue that chemical fertilizer is a credence good for which *ex post* detection of excessive use is costly for local farmers. Household-level data of rice farmers collected in three Chinese provinces is used to test whether and to what extent the intensities of fertilizer use by farmers are related to the sources from which they learn about how much fertilizer is needed. We find that farmers learning from fertilizer sellers on average have a 7.4% higher fertilizer use intensity, while farmers relying on information from public extension services have an 8.9% lower fertilizer use intensity; the use intensity of farmers relying on own farming experience is 10.6% higher on average. We explore mechanisms that are expected to mitigate sellers' adverse incentives in the credence goods market, e.g., market competition, but find no evidence that these mechanisms significantly reduce farmers' fertilizer use intensity. We conclude that more attention may need to be paid to local fertilizer markets to reduce fertilizer use in China.

* This chapter is based on the working paper:
Chen, M., Zhu, X., & Heerink, N. (2021). Fertilizer use in a credence good market: evidence from Chinese rice farmers.

5.1. INTRODUCTION

Excessive use of chemical fertilizers can cause sizable losses for both the economy and the environment (World Bank, 2007; Sutton et al., 2011). In China, there is well-documented evidence showing that fertilizer overuse is prevalent in many major agricultural production regions (see Ju et al., 2009; Zhang et al., 2013; Chen et al., 2014). To remedy this, the government has initiated various types of programs that are aimed at farmers to reduce fertilizer use. Notable examples over the past fifteen years include the nationwide formula fertilization program that started in 2005, a large-scale field experiment with integrated soil-crop system management practices (see Cui et al., 2018), and land fallowing and crop rotation programs aiming at achieving zero-growth in fertilizer use by 2020. Although these efforts have contributed significantly to the decrease in fertilizer use at the *aggregate* level, recent evidence shows no promising reduction at the *disaggregated* level, at least for the major grain crops (see Figure 5.1). Indeed, estimated household-level fertilizer use efficiencies, especially for rice production, still stagnate at low levels due to excessive use (e.g., in Ma et al., 2014 and Ren et al., 2020a), indicating huge potentials for Chinese farmers to reduce fertilizer use.

Figure 5.1. Per hectare chemical fertilizer use for major crops in China (2005-2017)



Data source: Compiled Files of National Agricultural Costs and Revenues (NDRC, 2011 & 2018).
Note: fertilizer use is measured by (NPK) nutrients quantity from various types of chemical fertilizers.

The limited success of these farmer-targeted fertilizer-reducing programs raises one pertinent but less studied question: to what extent do fertilizer sellers influence farmers' fertilizer use decisions in China? There are two main observations that justify a closer examination of this question. First, the level of fertilizer use is often correlated with market conditions. In regions around the world where fertilizer is significantly underused, the fertilizer market is usually poorly developed; such a market is characterized by poor accessibility, supply of fake fertilizer, high logistic costs and prices, and weak rural distribution networks (World Bank, 2007; Bold et al., 2017). On the contrary, China has established "a robust industry with burgeoning fertilizer distribution network" (Li et al., 2013, p.976) via market liberalization and subsidizing both farmers and fertilizer producers; fertilizer sellers in this market actively promote products and farmers enjoy improved fertilizer accessibility, quality, and low prices (Li et al., 2013; Smith and Siciliano, 2015). Second, applying the right fertilizer type with the right rate at the right time and place can be a rather complex task for farmers (IPNI, 2012). It requires farmers to learn frequently from their own experience and/or from other external information sources. One of the most important external sources is the public agricultural extension services (AES) system. However, if this system malfunctions, as in many developing countries, farmers are then forced to learn from alternative sources such as peer farmers and fertilizer sellers.

China once built a large and efficient public AES system that extended even into remote rural areas. However, it soon brought heavy financial burdens to the government and started to shrink in the late 1980s following a series of reforms that aim to realizing financial self-sufficiency in the system (Hu et al., 2004; Hu et al., 2009). One of the unique features of these reforms is to encourage AES agents to participate in commercialized activities such as selling fertilizers (and other agricultural inputs) to farmers, which was still largely controlled by the government in planned manners at that time. These commercialized AES agents (and later also their family members and relatives) gradually became first-generation private fertilizer sellers when the agricultural input market was liberalized throughout the 2000s (see Section 5.2 for more discussion). The contraction of the public AES system, the expansion of the fertilizer market, and the dual roles of fertilizer sellers prompted farmers to learn the use of fertilizers more frequently from sellers, especially small retailers in the rural fertilizer market.

In this chapter, we seek to examine whether and to what extent sellers in this unique fertilizer market influence farmers' fertilizer use behavior. Our conceptual and analytical framework is set up by considering chemical fertilizer as a type of *credence good*,[32] for which even *ex post* detection of excessive use is difficult for farmers. Under this concept, and given that fertilizer sellers in China's local fertilizer market play dual roles in diagnosis (assess farmers' fertilizer needs) and treatment (sell chemical fertilizers), we assume that sellers would over-recommend and oversell fertilizers to farmers because: (*i*) chemical fertilizer has credence properties, (*ii*) expert sellers have information advantage over

[32] Darby and Karni (1973) summarized credence qualities as what are expensive to judge even after purchase of the goods or services. They stated that "credence qualities arise whenever a good is utilized either in combination with other goods of uncertain properties to produce measurable output or in a production process in which output, at least in a subjective sense, is stochastic, or where both occur." (See p. 69).

farmers, and (*iii*) sellers have strong financial incentives to do so, as are embedded in early financial reforms and in current burgeoning fertilizer distribution networks. From the perspective of farmers, this assumption implies that farmers learning from fertilizer sellers in such a market are likely to use more fertilizer than their counterparts.

To empirically verify this, we use household (and village) survey data of rice farmers collected in three provinces of China (Liaoning, Jiangsu, and Jiangxi) to estimate the effect of obtaining fertilizer use information from sellers on farmers' fertilizer use intensity. To compare to other information sources, in the empirical model, we also include other three alternative information sources, i.e., public AES agents, social network of relatives and friends, and own farming experience. The major challenge in our estimation is that farmers can self-select from different sources of information. Therefore, we control for potentially confounding factors in an augmented model to reduce omitted variable bias. The main finding that consistently emerges from these analyses is that rice farmers who obtain information from fertilizer sellers on average spend 7.4% more on fertilizer per unit of cultivated land than those who do not rely on seller information, holding other factors constant. Interestingly, we also find that learning from their own experience is associated with a 10.6% higher intensity of fertilizer use.

Following these findings, we also examine how fertilizer sellers' incentives to "oversell" to farmers may be mitigated. We rely on established theories of credence goods to examine the interactive effects of introducing public AES agents, fostering market competition among sellers, and nurturing social trust toward different information sources. We find no empirical evidence that consulting both fertilizer sellers and AES agents would reduce the intensity of fertilizer use, nor do we find evidence that increased market competition among sellers and reduced social trust toward sellers reduce the intensity of fertilizer use.

Our main contributions to the literature are twofold. First, we conceptually take chemical fertilizer as a credence good in its quantity dimension by arguing that excessive use of fertilizer can hardly be verified *ex post*, which may be particularly true for smallholders in many developing regions around the world. The concept of credence goods has been applied in studies of various types of goods and services markets such as healthcare services, auto repair, legal services, etc., to our knowledge, this is the first study considering chemical fertilizer as a type of credence good. In this manner, our study contrasts with the recent study of de Brauw and Kramer (2018) who explicitly argue that chemical fertilizer is an experience good such that its quality information becomes known to farmers after use; while their study attempts to explain the low fertilizer adoption rate in Bangladesh, ours alternatively provides additional thoughts about why chemical fertilizer is persistently used excessively in China. Second, our empirical finding complements the vast literature that has mainly focused on targeting farmers to reduce fertilizer use intensity in China (e.g., Huang et al., 2008; Pan et al., 2017; Pan and Zhang, 2018). It suggests that targeting fertilizer sellers, and perhaps more broadly the entire fertilizer market, from producers to retailers, may provide an alternative way to reduce the persistently high intensity of chemical fertilizer use in China's agricultural production. In this direction, the implications of our study are more closely related to those of Jin et al. (2015).

The rest of this chapter proceeds with a description of China's local fertilizer market in Section 5.2. Section 5.3 sets up a conceptual framework. In Section 5.4, we describe our data sets and empirical strategy, followed by a discussion of the estimation results in Section 5.5. We conclude in Section 5.6.

5.2. RISE OF CHINA LOCAL FERTILIZER MARKET

Before the late 1980s, the production and distribution of chemical fertilizer in China was carried out exclusively by the government in planned manners. Meanwhile, China had also established the world's largest public AES system that was extended to almost all counties and rural townships. However, operating such a huge system caused financial burdens for the government (Hu et al., 2009). To alleviate these burdens, the government initiated a series of financial self-sufficiency reforms in the AES system; one of the key policy instruments was to allow overstaffed AES stations below the county level to sell agricultural input when they provided public AES to farmers (see Hu et al., 2004; Hu et al., 2009; Jin et al., 2015).

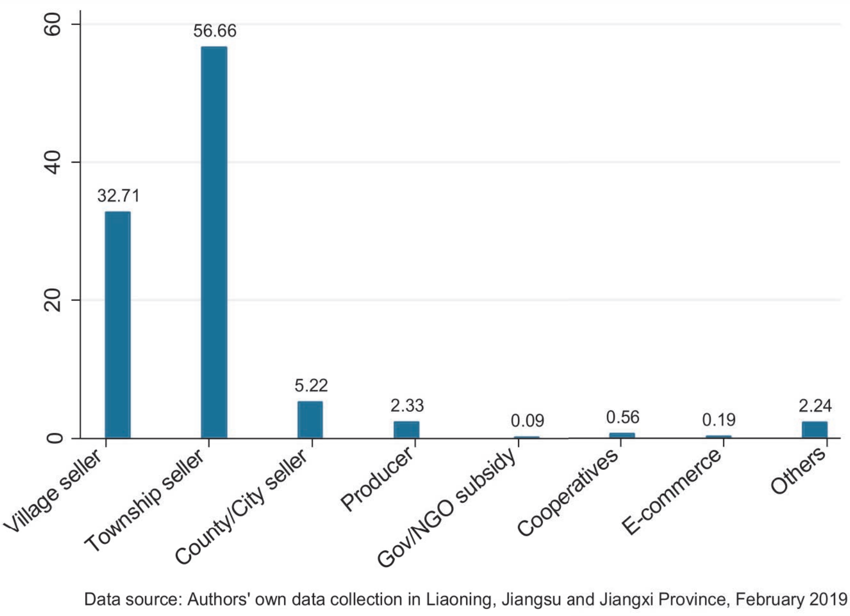
However, these reforms were criticized for creating misaligned financial incentives for AES agents to over-recommend and oversell fertilizer to farmers while reducing their time allocation to public AES (Hu et al., 2004; Hu et al., 2009). When the fertilizer retailing market was gradually liberalized toward private sellers in the following years, many of these commercialized AES agents became full-time first-generation private sellers in the rural fertilizer market (Chen, 2018),[33] joined later by their family members and relatives.

Meanwhile, fertilizer production also grew rapidly in the 1990s and 2000s in China. This was driven in part by the increasing demands under agricultural household support policies and in part by fertilizer industry subsidies (see Li et al., 2013; Smith and Siciliano, 2015). For example, the number of compound fertilizer manufacturers in China increased from 614 to more than 6,000 between 2003-2010 (Li et al., 2013). Rapid growth in production prompted further expansion of fertilizer distribution networks, for which the timing also coincided with the input market liberalization reforms that allowed the entry of private sellers in the late 2000s. These reforms and the growth of production contributed together to create a fertilizer market with growing distribution networks that reached remote rural villages.

[33] It was only recently that some local governments began to decouple its AES system from selling agricultural inputs.

Today, the fertilizer market in China typically consists of domestic producers at the top, several levels of distributors in the middle, and farmers at the bottom. Farmers have easy access to fertilizer from various sources, such as producers, city/county level wholesalers, a large number of township/village-level retailers (local sellers), or the cooperatives that farmers belong to. However, the largest share of transactions is conducted at the rural township/village level with local sellers. For example, in our interview with 1,073 farming households in three Chinese provinces, Liaoning, Jiangsu and Jiangxi, in February 2019 (see more details in Section 5.4), approximately 90% of them reported buying chemical fertilizer mainly from local sellers (see Figure 5.2); only a small proportion of households bought fertilizer directly from higher-level wholesalers located in the county or city centers.

Figure 5.2. Sources of obtaining chemical fertilizer for farmers in China



5.3. CONCEPTUAL FRAMEWORK

Motivated by the unique local fertilizer market in China, in this section, let us consider chemical fertilizer as a type of credence good, for which not only ex ante estimation of how much quantity to use is difficult for farmers, but also *ex post* detection of excessive use, if any, is either very costly or impossible. We argue that this concept is appropriate to describe chemical fertilizers because in evaluating the effectiveness of fertilizer use, crop yield is often taken as the main criterion by farmers when public AES is unavailable. However, the yield itself can be stochastic since it is also determined by other production factors of uncertain properties, such as seed quality, soil quality, pests, and weather condition (see discussion in Darby and Karni, 1973). Furthermore, crop yield is usually inert even if the amount of applied fertilizer has reached beyond the optimal agronomic level, as long as excessive use does not reach an extremely high and toxic level that can reduce yield (IPNI, 2012). In such a case, excessive nutrients that cannot be absorbed by crops can cycle into atmosphere, soil, and surface and ground waterbodies, and cause environmental problems such as greenhouse gas emission, soil acidification, and water eutrophication (Good and Beatty, 2011; Cui et al., 2018). However, these adverse effects can hardly be observed in the short run by farmers; and even if observed in the long run, farmers may lack the knowledge to link them to excessive use of fertilizer.

The established theory of credence goods implies that when diagnosis and treatment are jointly provided by sellers in the market and sellers have information advantage over buyers on the credence properties of the traded product, then there exists strong motivation for sellers to overtreat buyers (Darby and Karni, 1973; Emons, 1997; Dulleck and Kerschbamer, 2006). Moreover, the existence of financial incentives that are reinforced by exogenous income shocks may aggravate this overtreatment motivation (e.g., in Gruber and Owings, 1996; Clemens and Gottlieb, 2014; and Currie et al., 2014). Our discussion in Section 5.2 shows that, in China's local fertilizer market, the initial group of sellers grew directly from within the public AES system due to financial self-sufficiency reforms. Such unique reforms not only provided misaligned financial incentives for sellers to over-recommend and oversell fertilizer to farmers, but also integrated the provision of extension services (diagnosis) and the selling of chemical fertilizer (treatment) into the hands of sellers, who are experts as well given their experiences in the AES system. Although the fertilizer distribution network has expanded to date, many latecomers in the market are closely connected to the AES system. Sellers in such a market are likely to extract the advantages embedded in asymmetric information and economies of scope to maximize profit by overstating the truly needed fertilizer quantity. This behavioral assumption indirectly implies that if farmers rely on fertilizer sellers as an information source to learn how much chemical fertilizer is needed for certain agricultural production activities, they are then likely to be overtreated and induced to use more fertilizer than those who do not rely on sellers for instructions.

Learning-by-doing can be more complex when the technology has credence properties. On the one hand, some farmers may still carefully experiment and update their beliefs in the learning process to target the correct quantity of fertilizer to be used. On the other hand, farmers who report to learn from their own experience may actually fail to reduce fertilizer use because realized crop yields on their farms cannot effectively reflect excessive fertilizer use due to the credence property of chemical fertilizer. In addition, farmers learning from peer farmers in their social networks (learning-from-others) may also fail to do so, depending on the distribution and accuracy of information conveyed by those social networks. If farmers and their peers learn from the same group of sellers, then social networks would generate little peer effect on reducing fertilizer use and may even lead to persistence in excessive use. These in general implies that the standard "target-input" model of learning theory[34] that focusing on farmers may not be applied effectively to understand farmers' fertilizer use behaviors when the technology itself has credence properties. Instead, conventional wisdom in credence goods theories may provide alternative ways to reduce fertilizer use by targeting sellers.

To mitigate expert sellers' incentives to overtreat buyers, one intuitive approach suggested by credence goods theories is to separate diagnosis and treatment (e.g., Emons, 1997). In fertilizer market, this may be realized by introducing expert AES agents, who are assumed financially non-incentivized, independent from and non-collusive with incumbent fertilizer sellers. If farmers rely on this information source for fertilizer use instructions, they are likely to use less fertilizer than those who do not. Moreover, as is shown in Krishna and Morgan (2001), if farmers consulted both fertilizer sellers and AES agents and their recommendations are in opposite directions, it is also likely that farmers have a lower fertilizer use intensity.

Another mitigating mechanism is to foster market competition among sellers with different opinions (see Wolinsky, 1993; Dulleck et al., 2011; Rasch and Waibel, 2018). Although economies of scope could be one of the reasons for overtreatment, more intense competition between fertilizer sellers can reduce farmers' cost of searching for additional opinions on fertilizer use intensity. Farmers can partly separate diagnosis and treatment by consulting more sellers of heterogeneous opinions with little cost before making the purchase decision, and therefore are likely to better target the right fertilizer intensity. However, when all sellers systematically over-recommend, consulting more sellers might never be beneficial (see Krishna and Morgan, 2001), and in this case, stronger market competition does not help farmers determine the right fertilizer use.

However, the effectiveness of these mechanisms can be compromised by farmers' trust in information sources from sellers, on the one hand, while on the other hand, it can also be enhanced if such trust is nurtured toward public AES agents. Farmers would always accept the recommended treatment with full trust (see Fong et al., 2020). For example, Jin et al. (2015) find that pesticide overuse among some cotton farmers in China is jointly driven by the precision of the pesticide seller's recommendation and the trust toward such information: overuse occurs when the information is accurate but farmers do not follow (low level of trust) or the information is distorted but farmers follow closely (high level of trust).

[34] See for example Foster and Rosenzweig (1995), Bandiera and Rasul (2006) and Vasilaky and Leonard (2018).

5.4. EMPIRICAL STRATEGY

In this section, we combine a household-level data set and a village-level data set to empirically test the theory that we proposed in the previous section. We first describe how we have collected the data and then set up our empirical models.

5.4.1. DATA COLLECTION

The data sets that we use were collected in February 2019 from six counties in three provinces, including Liaoning, Jiangsu, and Jiangxi. These provinces and counties were selected in an earlier survey conducted in 2014/2015 as representatives of different agricultural production conditions, respectively, in Northeast, East and Southeast China. Two counties in each province were selected to reflect differences within the province in topology, distance to the provincial capital, and economic development levels (see more discussions in Zhou et al., 2019). We set up our 2019 survey in the same counties. This is not only because these counties fit into the overarching purpose of our project related to farm size enlargement, agricultural production efficiency, and environmental spillover issues in rural China, but also because it is cost-efficient for pre-survey works such as pilot studies and relationship building with local officials.

However, we resampled towns, villages, and households within counties and used new survey questions in the 2019 survey, primarily because these lower-level administrations in the 2014/15 survey did not fit well into our project purpose and did not contain necessary information for this study. In each of the six counties, we randomly selected five towns with a systematic sampling method based on their rankings in an ordered list of average household land endowment in the county. Then, in each town, we randomly selected four villages using the same approach. In the last step, twelve households were selected from each village using the stratified random sampling method. The three strata we used include households who rented in land only, rented out land only, and had no land rental activities.[35]

We effectively interviewed 1,420 households[36] and 120 village officials in 120 villages. We note that in the household-level data set, 347 households did not engage in agricultural production in the preceding season (most of them are from the stratum of renting out land only). For the remaining 1,073 households, all reported having cultivated one or two types of grains (rice, wheat, and/or maize) as their main agricultural products. In the main analysis, we drop the 237 wheat and maize farmers and focus only on the 836 rice farming

[35] There is only a very small fraction of households who both rented in and rented out land. Therefore, we group them into one of the two strata, i.e., rented-in only or rented-out only, depending on which of the two dominated.

[36] We surveyed 1,440 households, but 20 households were dropped from the data set because of invalid responses.

households, of which 212 are from Liaoning, 254 from Jiangsu, and 370 from Jiangxi. This is mainly because in each province rice was the most widely cultivated crop among the households surveyed, and in Jiangxi Province it was even the only grain produced.

For the rice farmers interviewed, we have information on the villages where they are located, such as village population, infrastructure, agricultural land and various types of markets; we also have their household and farm information, such as on household rosters, agricultural inputs and outputs, respondents' risk and time preferences, etc. We particularly collected detailed information on households' use of chemical fertilizer. For example, we asked in the household survey, "What information sources do you usually rely on to learn how much fertilizer to use? Please select all that apply." The respondent was presented with a list of four choices, including fertilizer seller, public AES agents, relatives and friends, and own experience.[37] We rely on this information to construct indicators of different information sources, and empirically bridge them to farmers' fertilizer use behavior according to our theoretical framework in Section 5.3.

5.4.2. MAIN MODEL

To estimate the effect of different information sources on households' fertilizer use decisions, we specify the following linear model:

$$\ln Y_i = \beta_0 + \beta_1 seller_i + \beta_2 ext_i + \beta_3 network_i + \beta_4 own_i + \boldsymbol{\gamma}'\boldsymbol{Z} + \mu_i \qquad (5.1)$$

where subscript i denotes household. Y is fertilizer use intensity, measured by per unit land fertilizer cost in rice production.[38] Variables $seller$, ext, $network$ and own are four dichotomous variables denoting respectively four information sources. They are not mutually exclusive, so a household that obtains information from two or more sources would have values equal to one for more than one of these four variables. $\boldsymbol{Z}$ is a vector set of control variables that include farm and household characteristics and village-specific factors, which are controlled mainly to reduce potential biases caused by omitted variables. For example, large farm operators in the literature are often considered to be more sensitive to changes in fertilizer prices and therefore pay more attention to the intensity of fertilizer use (Ju et al., 2016; Wu et al., 2018); they may prefer information from professional sources, such as government AES agents, while undermining information from sellers. Farm operators who are more educated and better trained in agriculture not only may use fertilizer more accurately but also are more likely to consult professional AES agents or

[37] We asked the fifth option: other information sources. But unfortunately, the options of own experience and other information sources were mistakenly coded with the same value. In our analysis, we interpret the latter as information based on own experience. According to our field observation, farmers very rarely obtain their fertilizer use information from other information sources than the four we used.

[38] For double-season rice, which is mainly produced in Jiangxi Province, we divide total fertilizer cost by total land input size in the two seasons.

trust their own farming experience, while risk averse farmers may have specific preference over certain types of information sources while they also tend to use more fertilizer to stabilize crop yield (Sheriff, 2005). In addition, the local information infrastructure related to the availability of extension services and the accessibility to the fertilizer market may also matter. For example, a longer travel distance to the fertilizer market can limit access to seller information, while it can also be associated with less fertilizer use due to increased transportation costs. Table A.5.1 in Appendix A summarizes the definitions of all variables used in equation (5.1).

Our primary interest is to gauge the effect of fertilizer sellers (β_1) as an information source on farmers' fertilizer use intensity. One must note again that the four dummy information sources that we include in equation (5.1) are non-mutually exclusive, i.e., choosing one source does not rule out the possibility of choosing others at the same time (see also Section 5.4.1). Therefore, the interpretation of estimated parameters for each information source is simply by setting up their corresponding null counterparts as the base groups. More specifically, given the theoretical reasoning in Section 5.3, we expect $\beta_1 > 0$, i.e., farmers learning from sellers about how much fertilizer is needed would use $100 \cdot \beta_1\%$ more fertilizer than those who do not learn from sellers, holding other factors constant. Our secondary interest is to quantify the effects of other information sources, i.e., public AES agents (β_2), relatives/friends (β_3) and own experience (β_4), on fertilizer use intensity. First, learning from public AES agents is assumed to have a negative effect because AES agents as the third party can work as a mitigation means against overtreatment by fertilizer sellers. Second, the effect of learning from social network of relatives/friends is unknown in this model specification without more information about how the network itself accumulates knowledge in our data set. Third, learning from own experience can have either negative or positive effect on fertilizer use intensity, depending on whether farmers frequently experiment and update their knowledge about the correct intensity, or they simply follow (previous or current) sellers' instructions in the credence good market.

5.4.3. MITIGATION MECHANISMS

In this subsection, we empirically model three mechanisms that potentially mitigate the effect of fertilizer sellers. First, we test to what extent farmers consulting *both* sellers and public AES agents would have a lower intensity of fertilizer use, since their recommendations are considered biased in opposite directions (see Section 3). To model this, we interact $seller$ and ext and estimate the following model:

$$\ln Y_i = \delta_0 + \delta_1 seller_i + \delta_2 ext_i + \delta_3 network_i + \delta_4 own_i + \delta_5 seller_i \times ext_i + \boldsymbol{\eta}'\boldsymbol{Z} + \epsilon_i \tag{5.2}$$

where $seller \times ext$ is the interaction term; other variables and parameters are defined similarly as in equation (5.1). We expect $\delta_5 < 0$ accordingly, i.e., conditional on consulting public AES agents, fertilizer sellers' effect would be lower ($\delta_1 + \delta_5 < \delta_1$). Second, we test the effect of market competition intensity among sellers on fertilizer use intensity, using the following model:

$$\ln Y_i = \alpha_0 + \alpha_1 seller_i + \alpha_2 ext_i + \alpha_3 network_i + \alpha_4 own_i + \alpha_5 seller_i \times nseller\_100_i + \boldsymbol{\theta}'\boldsymbol{Z} + \xi_i \tag{5.3}$$

where $nseller\_100$ denotes market competition intensity, which is measured by the density of fertilizer sellers per hundred households in a village. Since we expect most sellers in China's local fertilizer market are systematically overselling, the expected sign of α_5 is positive. Third, we estimate to what extent farmers' trust in different information sources would influence the effects of these sources on the intensity of fertilizer use, since the effectiveness of different information sources may depend on farmers' trust in them. We specify the model as follows:

$$\ln Y_i = \zeta_0 + \zeta_1 seller_i + \zeta_2 ext_i + \zeta_3 network_i + \zeta_4 own_i + \zeta_5 seller_i \times s\_trust_i + \zeta_6 ext_i \times e\_trust_i + \zeta_7 network_i \times n\_trust_i + \boldsymbol{\lambda}'\boldsymbol{Z} + \upsilon_i \tag{5.4}$$

where s_trust, e_trust and n_trust are dummy variables measured respectively by asking whether the respondents would adopt recommendations from fertilizer sellers, public AES agents and social network of relatives and friends. We expect that the signs of ζ_5, ζ_6 and ζ_7 will be the same as ζ_1, ζ_2 and ζ_3 respectively, implying that trust toward certain information source always reinforces its effect on fertilizer use intensity. We estimate equations (5.1) - (5.4) with ordinary least square (OLS) method and cluster standard errors at the village level given our sampling approach.

5.5. RESULTS AND DISCUSSION

5.5.1. MAIN RESULTS

Table 5.1 presents the OLS estimation results of equation (5.1) by full sample and by province, respectively. Again, we emphasize that our measured information sources are not mutually exclusive and therefore the base group in interpreting estimated parameters for each information source is simply their corresponding null counterparts. In particular, in the full sample estimation, we find that, keeping other factors constant, rice farmers who rely on fertilizer sellers for information on average have 7.4% higher fertilizer use intensity. That is to say, they spend more on fertilizer per unit of land than those who do not rely on fertilizer sellers, regardless of whether or not they obtain information from other sources. One of the key reasons might be that sellers, taking advantage of asymmetric information in a credence good market, behave strategically by over-recommending and overselling fertilizer to farmers (see also in Section 5.3).

Furthermore, we find that learning from public AES agents is significantly associated with a lower fertilizer use intensity of 8.9%. It confirms that the information provided by public AES experts may mitigate overtreatment by fertilizer sellers in the local fertilizer market. This finding may also be consistent with the observation that recently some public AES agents are required to gradually decouple extension services from profit-seeking activities such as selling agricultural inputs.[39] Interestingly, we also find that learning from one's own farming experience significantly increases intensity by 10.6% on average. This positive effect partly supports the prediction derived from the credence property of chemical fertilizer in Section 3; though farmers responded that they learn from their own experience, such experience may not effectively contribute to changes in the intensity of fertilizer use if the credence property dominates the learning process. Finally, we did not find evidence that learning from relatives and friends has a significant effect on the intensity of farmer fertilizer use.

Given that substantial geographical differences exist between the three provinces where the data were collected, we also separately estimated the models for each of the three provinces., Learning from fertilizer sellers is found to be positively associated with a higher fertilizer use intensity in Liaoning (6%) and Jiangxi (11.3%), but the effect is not statistically significant in Jiangsu Province. Learning from public AES agents only has a significant effect in Jiangsu Province. It was found to be associated with a 17.7% lower fertilizer use intensity. Information provided by relatives/friends and learning from own experience has a significant positive effect on fertilizer use intensity in Jiangxi Province alone. The use intensity is 12.6% higher (at a 10% significance level) for relatives/friends and 23.4% higher on average for farmers relying on their own experience in that province.

For parameter estimates of the control variables, either with full sample or by province, fertilizer price is found to explain a substantial proportion of the variation in fertilizer use intensity. For example, a 1% increase in fertilizer price is associated with a 74% increase in fertilizer cost per unit of land in the full sample. This is expected since the intensity of fertilizer use, our dependent variable in Table 5.1, is a cost measure that is calculated using this price information. But it also implies that, if we single out the price effect in our data and use fertilizer physical quantities to measure fertilizer use intensity, the effect of price may disappear. This is confirmed in Table B.5.1 (first column) in Appendix B, where we estimate equation (5.1) with the physical quantity of fertilizer as the dependent variable. In fact, the estimated parameter for fertilizer price is statistically insignificant in that model.

[39] For example, Guangdong Province regulated that AES agents were not allowed to sell agricultural inputs starting from January 2016. See http://www.gov.cn/xinwen/2015-12/28/content_5028585.htm (in Chinese, accessed on April 28, 2021).

Table 5.1. Effects of information sources on farmers' fertilizer use intensity – OLS regression of equation (5.1)

Dependent variable Fertilizer use intensity	Full sample	By Province Liaoning	 Jiangsu	 Jiangxi
Information sources				
Fertilizer sellers	0.074**	0.060*	0.050	0.113**
	(0.031)	(0.035)	(0.065)	(0.052)
Public AES agents	-0.089**	0.024	-0.177***	-0.028
	(0.040)	(0.055)	(0.055)	(0.11)
Relatives/friends	0.048	0.083	-0.000	0.126*
	(0.042)	(0.084)	(0.066)	(0.071)
Own experience	0.106**	0.014	0.050	0.234***
	(0.041)	(0.046)	(0.062)	(0.086)
Farm characteristics				
Log fertilizer price	0.741***	0.784***	0.973***	0.746**
	(0.17)	(0.13)	(0.14)	(0.28)
Log operational farm size	0.009	-0.012	0.039	0.022
	(0.012)	(0.013)	(0.029)	(0.023)
Low-quality land ratio	-0.027	0.061	-0.044	-0.056
	(0.068)	(0.090)	(0.11)	(0.084)
Irrigated land ratio	-0.006	-0.087	-0.056	0.003
	(0.047)	(0.11)	(0.096)	(0.063)
Rent-in land ratio	0.072*	0.120***	0.021	0.038
	(0.037)	(0.041)	(0.093)	(0.066)
Household characteristics				
Labor migration ratio	-0.047	-0.094	0.003	-0.096
	(0.057)	(0.075)	(0.055)	(0.11)
HH education	0.001	0.001	-0.006	0.009
	(0.0049)	(0.0086)	(0.0057)	(0.0092)
HH agricultural training	-0.024	0.025	-0.022	-0.060
	(0.032)	(0.035)	(0.044)	(0.071)
HH risk preference	-0.009	-0.017	0.003	-0.022
	(0.018)	(0.026)	(0.022)	(0.038)
Village-specific factors				
Market access	0.001	-0.004	0.006	0.001
	(0.0031)	(0.0056)	(0.0052)	(0.0040)
Land certificate	-0.179**	0.000	-0.053	-0.219**
	(0.080)	(.)	(0.068)	(0.10)
Number of AES agents	0.003	0.001	0.029	-0.078*
	(0.0062)	(0.0034)	(0.019)	(0.040)
County fixed effect	Yes	Yes	Yes	Yes
Constant	4.243***	4.370***	4.384***	4.425***
	(0.17)	(0.16)	(0.19)	(0.24)
Observations	836	212	254	370
R^2	0.174	0.288	0.334	0.133

Notes: cluster-robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Although operational farm sizes vary significantly both within and between provinces, we find no significant effect on fertilizer use intensity in the full sample and in provincial level models.[40] There is also no evidence that other farm characteristics are significantly associated with fertilizer use intensity of a farm, except for the farm-level land rental ratio which seems to positively affect fertilizer use intensity (by 7.2%) in the full sample estimate, but it is fully driven by that in Liaoning Province, where more than 50% of cultivated land is rented for a typical rice farm (see Table A.5.2 in Appendix A). The effects of household characteristics, including the household labor migration ratio, the level of education of household heads, the experience of agricultural training, and risk preference are all insignificant. For village-specific factors, there is no evidence that access to market significantly affects farmers' fertilizer use intensity. However, in Jiangxi Province, whether or not land certificates are issued and the number of AES agents in the village make big differences in fertilizer use intensity. In particular, farms in villages that have been issued a land certificate on average have a 21.9% lower fertilizer use intensity, while one more AES agent in a village reduces that average intensity by approximately 7.8%. Since both the number of villages having issued land certificates and the number of AES agents are lower in Jiangxi than in Jiangsu,[41] our results imply that improving these conditions in Jiangxi is effective for controlling fertilizer overuse.

In Table B.5.1 of Appendix B, we check the robustness of our estimation results by re-estimating the full sample model with two alternative measures for fertilizer use intensity: one is the fertilizer physical quantity (in kg/mu) and the other is the fertilizer cost directly reported by farmers (yuan/mu). The estimation results are robust to a large extent and confirm in particular what we have found so far for the effects of different information sources. Although the estimated magnitudes of using alternative fertilizer cost are much larger for fertilizer sellers and farmers' own experience, their signs are well preserved and hence do not significantly affect our main discussions above and below.

5.5.2. Public AES, market competition, and trust

In this subsection, we discuss the results from estimating equations (5.2) - (5.4) that are intended to explore mechanisms that mitigate sellers' fraudulent incentives. In the first column of Table 5.2, we find no significant effect of consulting both fertilizer sellers and public AES agents on fertilizer use intensity (the coefficient estimate of $seller \times ext$). As shown in the second column, there is also no evidence that the measured market

[40] Following Wu et al. (2018), who argue that operational farm size is endogenous and hence use farm size that was exogenously allocated by village committees in 1998 as an instrument variable, we adopt similar approaches (instrumenting operational farm sizes with allocated land sizes in 1998 and 2018, respectively) to check the robustness of our results. We find that this issue does not significantly affect our main results and conclusion.

[41] A comparison to Liaoning Province is more complicated since all surveyed villages did not issue land certificate.

competition intensity (number of fertilizer sellers per hundred households in a village) would significantly influence the fertilizer use intensity of those who reported learning from sellers. However, it is still debatable to what extent we can assure that either this finding violates Wolinsky (1993) prediction that higher-level competition among sellers decreases the probability of conducting fraudulent behaviors or it supports Krishna and Morgan (2001) that consulting multiple sellers that are biased toward the same direction in their recommendations will never be beneficial. This is because the proxy variable we adopt to measure fertilizer market competition is not ideal. Our data only allows us to control for sellers *within* the village, while a large proportion of farmers actually buy fertilizer from township-level sellers outside the village (56.66%; see Figure 5.2).

Table 5.2. Effects of mitigation mechanisms on farmer fertilizer use intensity – OLS regression of equations (5.2), (5.3), and (5.4) by full sample

Dependent variable: Fertilizer use intensity	**Equation (5.2)**	**Equation (5.3)**	**Equation (5.4)**
Information sources			
Fertilizer sellers	0.065*	0.081**	-0.013
	(0.038)	(0.032)	(0.068)
Public AES agents	-0.111*	-0.088**	-0.004
	(0.059)	(0.040)	(0.053)
Relatives/friends	0.042	0.048	-0.264***
	(0.042)	(0.042)	(0.099)
Own experience	0.099**	0.108***	0.094**
	(0.045)	(0.040)	(0.039)
Fertilizer sellers × Public AES agents	0.047		
	(0.090)		
Fertilizer sellers × Market competition		-0.021	
		(0.048)	
Fertilizer sellers × Trusting sellers			0.093
			(0.072)
Public AES agents × Trusting Public AES agents			-0.100
			(0.064)
Relatives/friends × Trusting relatives/friends			0.331***
			(0.11)
Controlled for farm, household, and village factors	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Constant	4.252***	4.241***	4.256***
	(0.17)	(0.17)	(0.17)
Observations	836	836	836
R^2	0.174	0.174	0.181

Notes: cluster-robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The last column of Table 5.2 reports the results of the estimate of interactive effects of external information sources and the trust toward them. To measure the latter, we use the information from the Yes/No survey question “Will you adopt the fertilizer use recommendations from fertilizer sellers (public AES agents, or relatives/friends)?” The data shows that 58.6% of households reported that they would adopt recommendations from fertilizer sellers, and the proportions for public AES agents and relatives/friends are respectively 63.5% and 56.8%. We find no evidence that information sources, such as fertilizer sellers and public AES agents, are associated with fertilizer use intensity when they interact with the corresponding trust measures. However, relatives/friends as sources of information are significantly associated with a 26.4% lower intensity of fertilizer use. But this effect becomes moderate and even changes the sign if farmers also report to trust their relatives and friends, noting that the bottom interactive term in the last column of Table 5.2 has an estimated parameter of 0.331 that is statistically significant at 1% level.

5.5.3. REMARKS

Though our estimated effects of different information sources, especially for fertilizer sellers, public AES agents, and their own experience, are significant and robust, interpreting them still needs to be careful. First, the estimated effects are correlational in nature, and interpretations are *ceteris paribus*. But it is still questionable to what extent we are able to hold other factors constant. Although we included a broad set of control variables, information sources may still be correlated with unobservable heterogeneities among households. A complete separation of these effects requires exogenous variations to be created for different information sources via, for example, randomized controlled experiments, which is beyond our study.

Second, our estimate implies that both fertilizer sellers and own experience contribute significantly to a higher level of fertilizer use intensity. One may wonder what own experience means exactly in this research context, and how it links to other external information sources. The cross-sectional characteristic of our data set does not allow us to trace the learning dynamics of farmers over time and to examine how farmers update their beliefs in the learning process based on different sources of information to decide the intensity of fertilizer use. If farmers’ own experience is simply a repetition and reflection of the misinformation of sellers, it would be difficult for us to disentangle the effect of fertilizer sellers from that of farmers themselves, which also leads to an underestimation of the seller effect and an overestimation of the learning-by-doing effect.

5.6. CONCLUSION, POLICY IMPLICATIONS AND FUTURE WORK

Conventional wisdom usually attributes the excessive use of fertilizers by farmers to the ineffectiveness of the measures that target farmers. This chapter adds to the literature by showing that on the supply side, fertilizer sellers play a crucial role in influencing the intensity of fertilizer use; the estimated effect implies that, keeping other factors constant, fertilizer sellers are associated with a 7.4% increase in the intensity of fertilizer use. This effect is both statistically and economically non-trivial. We argue that the reason lies in the uniqueness of the local fertilizer market in China, in which fertilizer sellers grew up within the public AES system. They have an information advantage over farmers to determine how much fertilizer is needed and play an inseparable role in selling the fertilizer. They are also able to over-recommend and oversell without *ex post* detection by farmers due to the credence property of chemical fertilizer. Consistent with this property may be the finding that farmers' learning from own experience is also associated with higher fertilizer use intensity.

Our finding suggests that, in addition to those many farmer-targeting approaches we have mentioned at the beginning of this chapter, targeting the local fertilizer market may provide other possibilities to control excessive fertilizer use in China. The central idea conveyed by our conceptual framework is to mitigate fertilizer sellers' overtreatment incentives and to reduce informational asymmetry between sellers and farmers over the credence property of chemical fertilizer. From a supply-side perspective, this requires regulating fertilizer sellers in the local fertilizer market, although practical policy instruments (e.g., market entry requirement, sales record keeping, environmental taxation) still need further discussion. The (re)introduction of credible third parties such as public AES agencies to provide cost-effective and trustworthy fertilizer use instructions may not only facilitate to separate diagnosis and treatment by fertilizer sellers but may also contribute to reshaping farmers' learning-by-doing process. Of course, technologies that can provide farmers with affordable ex ante tests of what type and how much fertilizer is needed or *ex post* detection of whether fertilizer is overused should not be left behind in such a policy design.

In fact, in recent years, the Chinese government has been observed to start to address issues of fertilizer overuse by initiating supply-side reforms, for example by partly canceling subsidies to fertilizer producers, improving environmental regulations, and decoupling public AES from selling fertilizers. However, it is still not very clear how these policy measures would channel through the supply chain and directly and indirectly affect fertilizer sellers in the rural local market. The scope of this chapter is to lay a groundwork by providing some early empirical evidence on whether and to what extent the fertilizer market, especially these local fertilizer sellers, affects the intensity of fertilizer use by farmers.

Future studies may focus on two directions: First, a key assumption in our theoretical reasoning is that fertilizer sellers are experts and have information advantages over farmers. But to what extent this assumption has reflected the reality for small retailers in the rural fertilizer market, many of whom are documented to be closely related to the public

AES system, is something per se that is worth further exploration by linking detailed farm-level data and fertilizer seller data. Second, the empirical estimation in this chapter has its limitations in determining whether the excessive fertilizer use observed in our data is driven by farmers' demands or by sellers' fraudulent behaviors in a credence good market (see for example Currie et al., 2014; Lopez et al., 2019). Without seller data, our analysis can only be considered indirect to link the high intensity of fertilizer use among farmers to fertilizer sellers. Furthermore, the causal relation between the fraudulent behavior of fertilizer sellers and the behavior of farmers in their fertilizer use needs to be further identified for the careful design of supply-side policy.

APPENDIX A

Table A.5.1. Definitions of variables used in estimating the effect of different information sources on fertilizer use intensity

Variable name	Definition
Dependent variable	
Fertilizer use intensity	Monetary cost of chemical fertilizer use per unit land
Independent variables	
Information sources	
Fertilizer sellers	=1 if farmers rely on fertilizer sellers to learn how much fertilizer to use; 0 otherwise
Public AES agents	=1 if farmers rely on public AES agents to learn how much fertilizer to use; 0 otherwise
Relatives / friends	=1 if farmers rely on relatives/friends to learn how much fertilizer to use; 0 otherwise
Own experience	=1 if farmers rely on own experience to learn how much fertilizer to use; 0 otherwise
Farm characteristics	
Fertilizer price	Weighted average price of all chemical fertilizers used in rice production [a]
Operational farm size	Operational farm size by the end of 2018
Low-quality land ratio	Ratio of low-quality land area to operational farm size
Irrigated land ratio	Ratio of irrigated land area to operational farm size
Rent-in land ratio	Ratio of rent-in land area to operational farm size
Household characteristics	
Labor migration ratio	Ratio of migrated labor to total labor (aged between 16-70) in 2018
HH education	Schooling years of household head
HH agricultural training	=1 if household head participated in agricultural trainings in the past; 0 otherwise
HH risk preference	Measured degree of risk aversion of household head [b]
Village-specific factors	
Market access	Distance (km) from village center to the closest market
Land certificate	=1 if the village has issued land certificates to its villagers; 0 otherwise
Number of AES agents	Number of government-designated AES agents in the village at present

a. We use an aggregated price index at the household level. To compute it, we first calculate the weights for each type of chemical fertilizer by dividing the quantity of nutrients in each type of fertilizer by the total quantity of nutrients. Then we multiply these fertilizer-type-specific weights by fertilizer-type-specific retailing prices reported by the farmers and add them up to obtain the aggregated fertilizer price at the household level.

b. This index measure follows Falk et al. (2016) and Falk et al. (2018). Lower index means higher risk aversion.

Table A.5.2 below gives the descriptive statistics of variables for equation (5.1) by full sample and by provinces. The average fertilizer cost for rice production in the full sample is 169.4 yuan/mu (or 384.2 US dollars per hectare[42]), which is 29% higher than the national average (131 yuan/mu; see NDRC, 2019). All farmers use fertilizer on their land, but there is a considerable spread in the data; fertilizer costs ranged from 27 to 600 yuan per mu. The largest variation in cost is found in Jiangxi Province, although the three provinces are similar on average cost.

For information sources, 44% of the farmers interviewed indicated that they rely on fertilizer sellers to learn how much fertilizer to use in the full sample. This proportion is approximately six times higher than the proportions of farmers who rely on public AES agents (7%) or relatives/friends (8%). Many farmers, approximately 60%, responded that they also learn from their own farming experience. The difference across provinces is large; the proportion of households that relied on fertilizer seller information in Liaoning (61%) is almost twice as large as that in Jiangxi (31%), while for own experience Jiangxi is significantly larger at 69% while Liaoning has only 49%. The low proportion observed for public AES agents in the full sample or in each province does not imply that farmers distrust this source. Instead, it may have reflected the fact that public AES is frequently missing. For example, when we asked farmers whether they would adopt fertilizer use recommendations from public AES agents, regardless of its availability, about 63.5% replied yes, even slightly higher than that for fertilizer sellers and relatives/friends.

The fertilizer price is 2.41 yuan/mu across the whole sample, with Jiangxi Province having the lowest average price and Liaoning Province having the highest. The average operational farm size in our full sample is 71 mu (or 4.73 hectare), which is significantly larger than the national average in 2018 (approximately 10 mu). This is partly due to our sampling strategy of disproportionally selecting an equal number of households from different strata based on land rental status. It is also because we have included Liaoning Province, which is characterized by much larger farms, in the survey. On average, the farm size in Liaoning is four times greater than that in Jiangxi, and Jiangsu is twice as large as Jiangxi. The variation is also large even within a province; for example, the standard deviation is approximately six times larger than the mean value in Jiangxi Province. Farms in Jiangxi Province are characterized on average with the highest ratio of low-quality land (14%). The land rental market varies slightly across provinces: in Jiangxi, a typical farm has 36% of its operational land area rented from others, while in Liaoning, this ratio is 52%; Jiangsu Province is in the middle, with 39% land rented.

[42] 1 hectare = 15 mu, and the nominal exchange rate we use is 1 USD = 6.613 yuan in 2018.

Table A.5.2. Descriptive statistics of variables used in estimating the effect of different information sources on fertilizer use intensity

Variable name	Unit	Full sample (N=836)			Mean (Std. Dev.) by province		
		Mean (Std. Dev.)	Min.	Max.	Liaoning (N=212)	Jiangsu (N=254)	Jiangxi (N=370)
Fertilizer use intensity	yuan/mu	169.40 (70.22)	27	630	162.87 (44.92)	175.54 (54.37)	168.93 (89.04)
Information sources [a]							
Fertilizer sellers	yes/no	0.44 (0.50)	0	1	0.61 (0.49)	0.49 (0.50)	0.31 (0.46)
Public AES agents	yes/no	0.07 (0.25)	0	1	0.07 (0.26)	0.09 (0.28)	0.05 (0.22)
Relatives/friends	yes/no	0.08 (0.27)	0	1	0.04 (0.19)	0.11 (0.31)	0.09 (0.29)
Own experience	yes/no	0.59 (0.49)	0	1	0.49 (0.50)	0.54 (0.50)	0.69 (0.46)
Farm characteristics							
Fertilizer price	yuan/kg	2.41 (0.48)	0.93	7.28	2.73 (0.38)	2.43 (0.25)	2.21 (0.55)
Operational farm size	mu	70.96 (205.35)	0.5	3480	135.53 (262.01)	69.66 (142.49)	34.85 (196.33)
Low-quality land ratio	ratio	0.09 (0.23)	0	1	0.04 (0.16)	0.04 (0.13)	0.14 (0.29)
Irrigated land ratio	ratio	0.87 (0.27)	0	1	0.87 (0.20)	0.93 (0.24)	0.83 (0.31)
Rent-in land ratio	ratio	0.41 (0.42)	0	1	0.52 (0.45)	0.39 (0.41)	0.36 (0.40)
Household characteristics							
Labor migration ratio	ratio	0.24 (0.26)	0	1	0.14 (0.22)	0.24 (0.28)	0.30 (0.26)
HH education	years	6.69 (3.19)	0	18	7.59 (2.59)	6.99 (3.41)	5.97 (3.18)
HH agricultural training	yes/no	0.37 (0.48)	0	1	0.50 (0.50)	0.50 (0.50)	0.22 (0.41)
HH risk preference b	index	0.02 (0.81)	-1.02	2.12	-0.07 (0.77)	-0.02 (0.84)	0.10 (0.80)
Village-specific factors [c]							
Market access	km	4.10 (3.92)	0	26	3.25 (2.95)	4.14 (3.67)	4.74 (4.73)
Land certificate	yes/no	0.65 (0.48)	0	1	0.00 (0.00)	0.97 (0.16)	0.85 (0.36)
Number of AES agents	persons	0.76 (2.10)	0	19	1.13 (3.47)	0.97 (1.44)	0.25 (0.63)

a. Summation of percentages in all four information sources does not equal to 1 because they are not mutually exclusive.

b. We measure the preferences of respondents, among of whom 90.54% are household heads, while 6.47% are the spouses of household heads. We have risk preference information for 835 respondents, and we imputed the missing one with sample average.

c. Full sample is based on 111 villages. Provincial sample is based on 32 villages in Liaoning, 39 villages in Jiangsu and 40 villages in Jiangxi.

37% of household heads reported to have participated in agricultural training. The standardized risk preference, which measures the degree of risk aversion following the Global Preference Survey module used in China by Falk et al. (2016) and Falk et al. (2018), shows that household heads in Liaoning (-0.07) and Jiangsu (-0.02) in general are more risk averse than those in Jiangxi (0.1).

In the bottom panel of Table A.5.2, our sample villages on average are about four kilometers away from the nearest market. Some villages have a market center such that the distance was recorded as zero. Intuitively, market access is more difficult in Jiangxi (4.74 km on average) due to its hilly geo-topological feature. Unexpectedly, though all sampled villages have completed the recent land certification program at the time of our survey, no village in Liaoning Province had completed issuing land certificates to its villagers,[43] while almost all villages had issued the certificates in the other two provinces. In terms of the number of AES agents designated by the government within villages in 2018, Jiangxi Province lagged far behind the other two provinces; almost four villages share one AES agent in Jiangxi, while in Liaoning and Jiangsu, on average, each village has one AES agent.

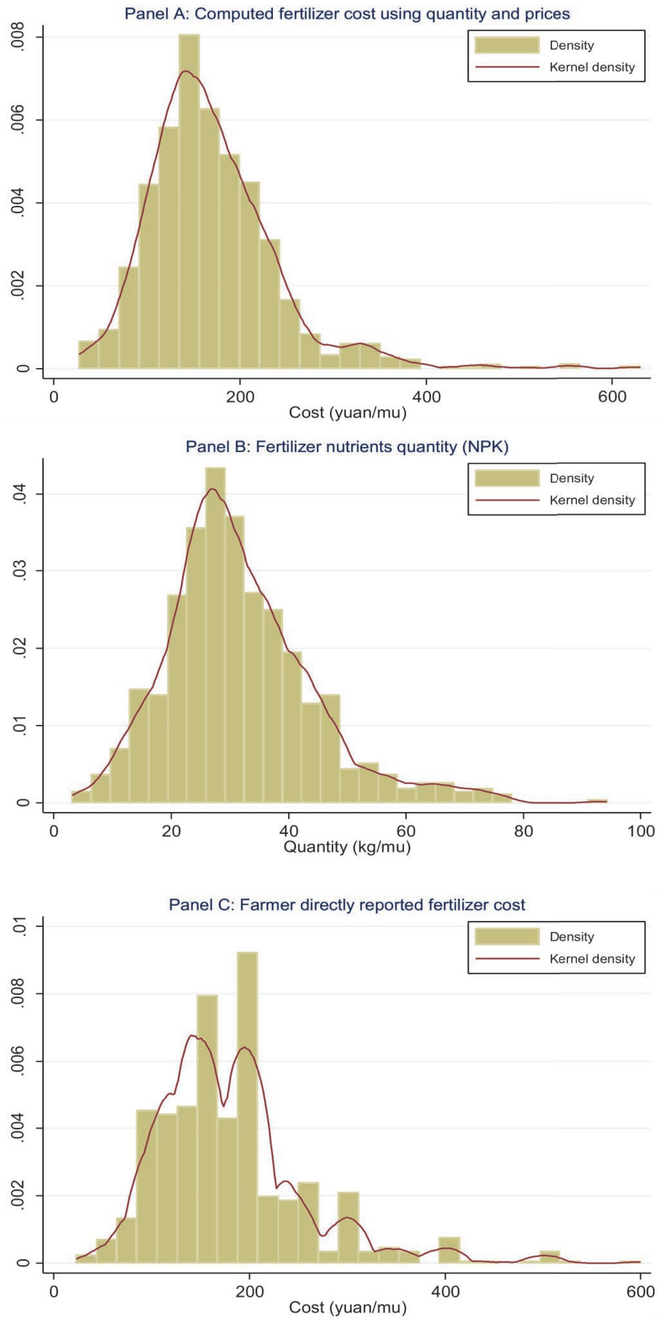
APPENDIX B

To examine the robustness of our major estimation results presented in Table 5.1, we perform the robustness check using two alternative measures of fertilizer use intensity: one is measured by physical fertilizer quantity in terms of NPK nutrients, and the other is measured by farmer-directly-reported fertilizer cost per unit of land. Figure B.5.1 compares the histograms and fitted kernel density plots of these two alternative measures with the one we use in the main estimate.

We can see that the main cost measure in Panel A and the alternative physical quantity measure in Panel B are much smoother. However, the distribution of farmer-directly-reported cost measure in Panel C (directly reported by farmers) has some spikes around the values of 150 yuan/mu (91 households) and 200 yuan/mu (143 households); this is because, in practice, farmers usually only report integer numbers by tens or twenties (e.g., 80, 100, 120, 150, 200). Table B.5.1 presents the OLS regression results by using these alternative intensity measures, and a brief discussion can be found in Section 5.1.

[43] The main reason reported by most villages was that the land certificates were still held by upper-level governments such as those in townships or counties.

Figure B.5.1. Distributional plots of different measures of fertilizer use intensity (N=836)



Data source: Authors' own data collection in Liaoning, Jiangsu and Jiangxi Province, February 2019.

Table B.5.1. OLS regression results with alternative measures of fertilizer use intensity

Dependent variable	**Log fertilizer physical quantity**	**Log alternative fertilizer cost**
Information sources		
Fertilizer sellers	0.072**	0.142***
	(0.035)	(0.036)
Public AES agents	-0.119***	-0.034
	(0.044)	(0.056)
Relatives/friends	0.041	-0.009
	(0.049)	(0.053)
Own experience	0.098**	0.151***
	(0.040)	(0.038)
Farm characteristics		
Log fertilizer price	-0.064	0.268
	(0.18)	(0.16)
Log operational farm size	0.012	0.024*
	(0.013)	(0.012)
Low-quality land ratio	-0.030	0.048
	(0.073)	(0.080)
Irrigated land ratio	-0.022	-0.051
	(0.050)	(0.059)
Rent-in land ratio	0.065*	-0.000
	(0.038)	(0.043)
Household characteristics		
Labor migration ratio	-0.066	-0.069
	(0.057)	(0.062)
HH education	0.000	0.000
	(0.0053)	(0.0054)
HH agricultural training	-0.001	-0.041
	(0.033)	(0.029)
HH risk preference	-0.004	-0.011
	(0.020)	(0.020)
Village-specific factors		
Market access	0.001	0.002
	(0.0037)	(0.0041)
Land certificate	-0.200**	-0.283***
	(0.087)	(0.076)
Number of AES agents	-0.018	0.007
	(0.012)	(0.0081)
County fixed effect	Yes	Yes
Constant	3.417***	4.762***
	(0.18)	(0.16)
Observations	836	836
R^2	0.098	0.105

Notes: Cluster-robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Chapter 6
General conclusions

This thesis studies the market failures in various types of input markets. The main objective of doing so is to obtain an improved understanding of the market failures that contribute to factor misallocation and excessive fertilizer use in Chinese agriculture. It has been well documented in the recent literature that market failures cause frictions and drive wedges into the marginal products of factors, and hence lead to factor misallocations (see for example Restuccia and Rogerson, 2008). The agriculture sector in China has long been characterized by small and relatively equally distributed farm sizes since the establishment of the Household Responsibility System in the late 1970s. In the early years, this system had contributed significantly to the country's agricultural output growth, rural poverty reduction, structural transformation, as well as the overall economic development. However, in recent years, the literature frequently documents that there is potentially severe factor misallocation under this system, which further leads to substantial losses in aggregate agricultural productivity (see for example Gai et al., 2017; Adamopoulos et al., 2020).

As debates about potential overestimation of misallocation arise in other countries (see for example Shenoy, 2017 in Thailand; and Gollin and Udry, 2021 in Tanzania and Uganda), we become curious about whether the documented extent of factor misallocation in Chinese agriculture has also been overestimated. We question to what extent productive factors are misallocated if the analysis is conducted at a different level and takes into account the trend of hired machinery services in China (see Chapter 3). We also question whether a land certification program that reduces land market failures and enhances tenure security influences factor allocation across farms and sectors in China, and do these effects, if any, translate into welfare implications (see Chapter 4). Beyond the issues in factor allocation, smallholder production also faces greater challenges on environmental issues. There is evidence that small farms are associated with more fertilizer use per unit of land (Ju et al., 2016; Wu et al., 2018). Given that fertilizer is extensively overused in China (see for example Zhang et al., 2013; Cui et al., 2018), this implies that smallholders not only are producing with suboptimal productivities, but are also putting greater pressure on China to achieve sustainable agricultural development. In Chapter 5, we question what type of market failure has potentially caused persistent excessive fertilizer use in China.

This thesis attempts to answer these fundamental questions for public policy suggestions. To do so, I organize the main part of this thesis into four independent chapters which are intended to answer four distinctive research questions. In the following sections, I first summarize my answers to the research questions that have been raised in Chapter 1 of this thesis. Then I synthesize the findings and discuss the policy implications from these findings. In the last section, I discuss the limitations of the thesis and recommendations for further research following the current studies.

6.1. QUESTIONS, FINDINGS, AND CONTRIBUTIONS

In Chapter 2, I review where the literature stands at present for studies of resource misallocation in the agricultural sector, which questions have been answered in the current research, with what methodologies, and what are the potential knowledge gaps. So far, there has been no comprehensive literature review that particularly focuses on the agricultural sector, although agriculture is of great importance for living standards in many less developed countries. Recent rapid development of the literature has made it possible to perform such a review. In this chapter, I find that the current literature has focused mostly on the misallocation of agricultural land, as well as its associated consequences on the efficient allocation of capital and labor. While many studies stress the importance of factor misallocation by using structural models to quantify the extent of it (the indirect approach in Chapter 2), several other studies directly examine the causes of factor misallocation by estimating the causal impact of certain public policies (the direct approach in Chapter 2). The main findings from these studies are that: first, there is substantial misallocation in the markets of productive factors in agriculture, particularly in the land market (see for example Gai et al., 2017; Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Ayerst et al., 2020); second, tenure-security-enhancing land reforms in general have significant positive impacts on factor allocation efficiency and aggregate productivity (see for example de Janvry et al., 2015; Chari et al., 2021). Despite these findings, some recent studies start to question whether the documented misallocation has been overestimated because of, for instance, measurement errors and adjustment costs. Mixed evidence has been documented so far in this strand of literature, while the number of studies keeps growing fast. The identified potential gaps that remain to be filled up from this literature review include measurement issues in the quality of capital, labor, and intermediate inputs, the role of farm entry and exit and their associated labor reallocation across sectors, welfare implications of factor misallocation, as well as estimates of misallocation from more diversified data sources, e.g., from regional surveys.

The literature review in Chapter 2 can be seen as an overarching guide for the studies in Chapter 3 and 4. In particular, Chapter 3 uses the indirect approach reviewed in Chapter 2 to quantify factor misallocation. It fills part of the gaps that have been identified in the end of Chapter 2 by asking whether productive factors such as land and capital are severely misallocated across farms in the agricultural sector of China. Are there any possibilities that the previous relevant studies (e.g., Gai et al., 2017; Adamopoulos et al., 2020; Chari et al., 2021) have overestimated the extent of factor misallocation? If so, what might be the potential reason(s)? To answer these questions, we use a farm-level survey data set collected from a region in the northern part of China to construct a cross section of farm-level TFPs. We then use it to evaluate to what extent land and capital are misallocated in the studied region. The main finding of this chapter is that, even though the region is characterized by extremely small and relatively equally distributed farm sizes, the measured extent of factor misallocation however is quite moderate: productivity gains in the region range from 7% for within-village efficient factor allocation to 10% for between-village efficient allocation. We argue that despite the geographic level of analysis that may contribute to this moderate finding, the main reason may be the active use of hired machinery services, which has been ignored in the literature of misallocation studies focusing on Chinese agriculture.

Chapter 4 complements Chapter 3 under the analytical structure laid out in Chapter 2. It uses the direct approach to examine the market failures that might influence the reallocation of factors. In particular, it questions whether the recent land certification program in China improves the land reallocation across farms and labor reallocation across agricultural and non-agricultural sectors (migration), and what is the impact of this program on intra-village cross-household income inequalities. Instead of measuring the program as dummy indicator to estimate its one-time shock effect, we measure it as a variable indicating for how many years the program had been completed in a village. Our purpose is to capture the impact of the program over time. Using household-level and village-level survey data sets collected in 2019 in three provinces in China, we estimate that the program has a significant inverted U-shaped impact on households' probability of renting in land. Nonetheless, the study finds no statistically significant evidence that the program affects households' decisions of land renting-out and migration, nor does the program significantly affect intra-village income inequality. Our study differs from and also contributes to the literature mainly in two ways: (*i*) the measure of the certification program is the time elapsed after program completion and we add a quadratic term to capture the non-linear impact of this program measure; and (*ii*) beyond estimating the impact of the program on factor allocation, we also include the analysis of equality.

Chapter 5 shifts the focus from the previous chapters. Instead of examining the factor inputs market failures for potential inefficiency in factor allocation and loss in aggregate productivity, this chapter particularly focuses on a market failure that potentially affects the use of a major intermediate inputs. It asks whether fertilizer sellers (or retailers) in rural China influence farmers' fertilizer use intensity. The main contribution of this study is that it considers chemical fertilizers as a type of credence good, which has been observed to characterize markets of legal services, auto repair, health care services, etc. Chemical fertilizer can be considered as a credence good because the *ex post* detection of excessive fertilizer use is costly for local farmers; this is partly due to the stochastic nature of agricultural production and partly due to the market failure that selling is characterized by asymmetric information in the local fertilizer market. Based on this novel concept, we find that farmers who learn from fertilizer sellers about how much fertilizer to use on average have 7.4% higher fertilizer use intensity, while farmers who rely on information from public extension services have 8.9% lower fertilizer use intensity; the use intensity of farmers who rely on own farming experience is 10.6% higher on average. We conclude that more attention may need to be paid to local fertilizer markets to reduce fertilizer use in China.

6.2. SYNTHESIS AND POLICY IMPLICATIONS

In general, Chapters 3-5 document the impacts of different types of market failures on factor allocation and input use in the same conceptual framework (see Figure 1.1 in Chapter 1). Market failures are implicitly embedded in Chapter 3, and we show that they potentially drive wedges in the marginal products of factors and lead to resource misallocation in the agriculture sector of China, even though we find that the extent of measured misallocation is moderate when compared to previous findings in the literature (e.g., Gai et al., 2017; Adamopoulos et al., 2020; Chari et al., 2021). However, Chapters 4 and 5 explicitly discuss the relevant market failures. In particular, Chapter 4 examines one underlying cause of land market failure, i.e., the unclearly defined land property rights, and studies what will be the impact on land rentals, migration, and intra-village income inequality if this land market failure is addressed by a land certification program. Chapter 5 studies the failure of the fertilizer market, that is, the asymmetric information between fertilizer sellers and farmers, and examines how such a failure of the market would influence the intensity of fertilizer use of Chinese farmers.

In addition to that, our major studies (Chapter 3-5) are put together under one conceptual framework, these independent studies are also interlinked to some extent either in empirical analyses or in policy implications. First, one of the central arguments in Chapter 3 is that the active use of hired machinery services among smallholders facilitates explaining the measured low level of factor misallocation in our study region. This same reason perhaps also explains why in Chapter 4 we find mixed impacts of the land certification program on farmers' land renting-in and land renting-out decisions, i.e., the program has a statistically significant and inverted U-shaped impact on farmers' land renting-in probability, while the impact on land renting-out probability is estimated as insignificant. Using hired machinery services to explain this mixed finding, on the one hand, if hired machinery services have the potential to make farming much less time-consuming and technologically and physically easier, then farmers who intend to rent in more land at the beginning may be more likely to do so because the marginal cost of farming seems much lower than marginal benefits when hired machinery services are easily and cheaply accessible. On the other hand, farmers who plan to rent out their land may become reluctant to carry out their plans, since farming becomes physically easier and less time-consuming with hired machinery services; the use of such services allows them to be employed somewhere else either in the agricultural or non-agricultural sector, while at the same time they retain their access to land use rights and enjoy cheaper agricultural products.

Second, farm size enlargement in many countries of the developing world, particularly those in sub-Saharan Africa and South and East Asia, is often considered a major target of policy making for improving agricultural productivity and standards of living. This may be because farm sizes in these countries are usually much smaller compared to countries in other regions, and historical data usually supports enlarged farm sizes along the development path (see Foster and Rosenzweig, 2021), and, moreover, recent literature has documented substantial resource misallocation in the agricultural sector of these countries, especially due to weak land institutions and other land market failures. For these reasons, government policies often aim to improve land tenure security to promote voluntary land transfers among farms. However, as we discussed in Chapter 3, removing institutional barriers in the land market and stimulating production efficiency by reallocating land to the most productive farmers can face sizable social and political challenges in these countries. As agricultural land for many poor households can play an important role in reducing risks by providing food security and social safety nets, smallholders can be rather reluctant to rent out their land even if land tenure is secured. When alternative employment opportunities in the non-agricultural sector are limited, as is especially the case in very poor countries, we may expect even much less land consolidations. But when tenure-security-enhancing land certification does not significantly affect farmers' land renting-outs and even household income (as in Chapter 4), fostering allocative efficiency through the capital market can be a more plausible policy alternative for increasing productivity. This is because an improvement in the functioning of the capital market can contribute to the equalization of capital-land ratios and hence to an increased aggregate output and productivity (as in Chapter 3). However, this discussion is not intended to downplay the importance of agricultural land policy reforms. On the contrary, better functioning land markets may contribute to, for instance, farm entry and exit and rural-urban migration through cross-sectoral resource reallocation or to incentivizing long-term agricultural investments. Such evidence can be found in the studies of, for example, Besley (1995) in Ghana, Deininger et al. (2011) in Ethiopia, de Janvry et al. (2015) in Mexico, and Chari et al. (2021) and Gao et al. (2021) in China.

Although we find in our study regions that enhancing land tenure security hardly promotes large-scale factor reallocation both within and across sectors (as in Chapter 4) and that factor misallocation explains only a moderate proportion of aggregate agricultural productivity (as in Chapter 3), our findings in Chapter 5 may imply possibilities of improving aggregate productivity through improvement of within-farm performance. This goes back to the conceptual framework in Chapter 1, although Chapter 5 does not explicitly link reduced fertilizer use intensity to farm-level production efficiency. Chapter 5 finds that information sources significantly affect the intensity of farmer fertilizer use. Under the background of persistent overuse of fertilizers in China, government policies targeting the supply side of the fertilizer market, i.e., fertilizer sellers, can effectively improve fertilizer use efficiency on farms, and hence reduce environmental pollution and improve on farm productivities as well as aggregate agricultural productivity.

6.3. LIMITATIONS AND RESEARCH RECOMMENDATIONS

The findings, conclusions, and syntheses that I have discussed in the previous sections are subject to a number of limitations. Some of the limitations have been discussed separately in the relevant chapters. In this section, I first briefly summarize a few key limitations in each of Chapters 3-5, and then lay out the general limitations of this thesis and the future research recommendations following the current studies. In Chapter 3, when we estimate the static productivity gains, a key assumption is that total resource endowments of land, capital, and the number of existing farms remain fixed in the examined region. However, these may change in reality due to shifts between one region and another. In Chapter 4, we measure the land certification program at the village level. However, maybe it is not the variation at the village level that determines households' factor reallocation behaviors, and instead it is the variation of perceived land tenure security at the household level that matters (Ma et al., 2015; Ma et al., 2016; Ren et al., 2020b). In Chapter 5, an explicit assumption is made that fertilizer sellers are experts and have information advantages over farmers. However, it remains unclear to what extent this assumption reflects the reality of small fertilizer retailers in the rural fertilizer market.

Beyond these limitations of the individual chapters, there are two major cross-chapter limitations that need to be stressed. First, this thesis focuses on input market failures, including the markets of land, capital, and intermediate inputs. No attention is paid to potential frictions in other markets, like output, labor, or credit markets. In the output commodity market, for example, smallholders are often assumed to be price takers. In recent years, however, competition in the output market has taken various forms. The emergence of farm cooperatives, contract farming, and agribusiness firms, which could arise as institutions that reduce market transaction costs and thereby reduce market frictions, may shift the competition structure in the local output market of China. In this situation, the measured factor misallocation in the agricultural sector of China may have reflected differences in market powers rather than in physical productivities (see Cusolito and Maloney, 2018). As another example, the credit market for smallholders is also changing in China in recent years. We have discussed one legislative reform in Chapter 4 that in some Chinese counties the farmers start to be allowed to collateralize their land management rights for credit. The question of how this will impact the reallocation of factors and promote growth of agricultural productivity surely deserves future exploration.

Second, a common feature of the empirical studies in Chapters 3 – 5 is that they all use cross-sectional survey data sets to estimate the relationship between observed economic variables. Although we test causal relationships derived from theories and strive to control for potentially confounding factors, our estimations may still face some shortcomings from unobservable factors. These problems might be particularly acute in Chapters 4 and 5, where econometric models are applied to analyzing observational data. Chapter 3 should be less exposed to the potential endogeneity problem, as some key steps are computational rather than econometrical. Nevertheless, using cross-sectional data may still lead to larger measurement errors in farm-level TFP estimation, as controlling for time-invariant farm-specific effects becomes impossible. Therefore, we look forward to robustness tests using panel data sets or even experimental data sets to establish concrete unbiased causal relationships between the variables that we examine in this thesis.

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SUMMARY

This thesis studies market failures, factor allocation, and input use in Chinese agriculture. In particular, it quantifies the extent to which productive factors are misallocated in the agricultural sector and examines market failures that are potentially linked to the misallocation of productive factors and the excessive use of chemical fertilizer. The research is motivated by two important characteristics of Chinese agriculture. First, operational farm sizes in China are generally very small, potentially implying a large misallocation of land among farmers that are heterogeneous in their productivities. Second, the use of chemical fertilizer per unit of land is not declining and continues to be very high, despite recent policies to control it. The lack of clearly defined land property rights and asymmetric information about fertilizer use may be important factors that explain these two phenomena, but have received little attention in the literature so far. The main objective of this thesis is therefore to obtain an improved understanding of market failures that contribute to factor misallocation and excessive fertilizer use in Chinese agriculture. To start, the thesis first gives a general introduction in Chapter 1, which is then followed by four independent, but related, studies in Chapters 2 - 5.

Chapter 2 reviews the recent literature that uses micro-level data to understand factor misallocation in the agricultural sector and its implications for aggregate agricultural productivity growth, both within China and beyond. The defining scope of misallocation is narrow and simple in this review: the misallocation of productive inputs such as land, capital, labor, and intermediate inputs across farms that are heterogeneous in their productivities and produce homogeneous agricultural goods. The reviewed literature is organized into two broad categories that include (*i*) the studies that use structural models to quantify the importance of factor misallocation in various contexts (denoted as the indirect approach), and (*ii*) the studies that attempt to identify the specific sources of factor misallocation in similar contexts (denoted as the direct approach). Following the structured review of the relevant literature, the chapter closes with a few questions for potential future studies.

Chapter 3 is motivated by the egalitarian allocation of agricultural land and small farm sizes in rural China, raising questions about the implications for overall productivity given that there exists potentially large heterogeneity in farm-level productivities. This chapter empirically examines to what extent land and capital are misallocated in a region within the North China Plain characterized by small and relatively equally distributed land sizes across households. Using a survey data set collected among wheat-maize double-cropping farms, it finds that the dispersion in farm-level total factor productivity is small, and the quantified gains in aggregate agricultural productivity that may be obtained by reallocating factors from less productive to more productive farms are moderate

relative to the current findings in the literature. Estimated productivity (output) gains in the studied region range from 7% for within-village reallocation to 10% for between-village reallocation. The chapter argues that these moderate findings can be largely explained by the high-level use of hired machinery services in the relatively small region.

Chapter 4 examines the impact of a land certification program on rural households' land rentals, migration, as well as intra-village income inequality. Using household-level and village-level survey data sets collected in 2019 in three provinces in China, it measures the key explanatory variable as the number of years the program has been completed in villages and therefore is able to capture the impact of the program over time. It estimates that the program has a significant inverted U-shaped impact on households' probability of renting in land. However, the study does not find statistically significant evidence that the program affects the decisions of households about land renting-out and migration, nor does the program significantly affect intra-village income inequality. These findings are robust to alternative measures and estimation strategies.

Chapter 5 examines whether the high intensity of chemical fertilizer use by Chinese farmers is related to the sources that provide information about fertilizer use, with a particular focus on the role of fertilizer sellers. It argues that chemical fertilizer is a credence good for which *ex post* detection of excessive use is costly for farmers. Household-level data of rice farmers collected in three Chinese provinces is used to test whether and to what extent fertilizer use intensities are related to the sources informing them how much fertilizer is needed. The study finds that farmers who are informed by fertilizer sellers on average have a 7.4% higher fertilizer use intensity, while farmers relying on information from public extensions services have an 8.9% lower fertilizer use intensity; the use intensity of farmers relying on their own farming experience is 10.6% higher on average. It explores mechanisms that are expected to mitigate sellers' adverse incentives in credence goods market, e.g., market competition, but finds no evidence that these mechanisms significantly reduce the intensity of farmer fertilizer use. The chapter concludes that more attention may need to be paid to local fertilizer markets to reduce fertilizer use in China.

Chapter 6 concludes the thesis by providing a general discussion and a synthesis of the major findings. It also lays out the implications for agricultural productivity policies and the limitations of the whole study.

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Minjie Chen

October 2021, Nanjing, China

Minjie Chen
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Wageningen School of Social Sciences

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Advanced Microeconomics UEC51806	WUR	2017	6
Impact Assessment of Policies and Programmes DEC32806	WUR	2018	6
Economics and Policy of Agricultural Development DEC53306	WUR	2018	6
Writing research proposal	WUR	2018	6
B) General research related competences			
WASS Introduction Course	WASS	2017	1
Advanced Behavioural Economic Theory	WASS	2018	4
Economics of Farm Households	WASS	2019	1
'The contribution of sellers to the overuse of chemical fertilizer in China'	IAAE-NJAU Symposium, Nanjing, China	2019	1
'Do small farm sizes imply large resource misallocation? Evidence from wheat-maize double cropping farms in the North China Plain'	Virtual 31st Triennial International Conference of Agricultural Economists (ICAE 2021)	2021	1
C) Career related competences/personal development			
Presenting with Impact	Wageningen in'to Language	2019	1
Teaching assistant for "Principles of Climate Change Economics and Policy ENR22806"	WUR	2019	1
Teaching assistant for "Methods, Techniques and Data Analysis for Field Research SDC21306"	WUR	2020	1
Teaching assistant for "Methodology for Field Research in the Social Sciences SDC33306"	WUR	2020	1
Total			**36**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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