Food Policy 112 (2022) 102350

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Do small and equally distributed farm sizes imply large resource misallocation? Evidence from wheat-maize double-cropping in the North China Plain[☆]

Minjie Chen[a,b], Nico Heerink[b], Xueqin Zhu[b], Shuyi Feng[c,*]

[a] School of Economics, Nanjing University of Finance and Economics, China
[b] Section Economics, Wageningen University & Research, Netherlands
[c] China Resources & Environment and Development Academy (REDA) and College of Public Administration, Nanjing Agricultural University, China

ARTICLE INFO

JEL codes:
O11
O13
O47

Keywords:
Resource misallocation
Smallholders
Machinery services
Agricultural productivity

ABSTRACT

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

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 (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., Gong, 2018; Sheng et al., 2020). 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 relevant 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 production factors toward more productive units (see reviews in Bartelsman and Doms, 2000; Tybout, 2000; Syverson, 2011; Restuccia and Rogerson, 2013, 2017). This recent strand of literature emphasizes the role of (between-firm) resource allocation efficiency across heterogeneous production units in stimulating aggregate TFP growth, instead of asking the traditional question why individual firms in an economy are less productive than their counterparts in another economy (Restuccia and Rogerson, 2013). Such efficiencies in resource allocation 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. Theoretically, efficient resource allocation between farms requires the marginal product of that resource to be equated across all farms, i.e., more resources are used by the more productive 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 there exist large inefficiencies in allocating resources (i.e., resource misallocation) across farms in China for

☆ We thank the editor, and three anonymous referees for helpful comments. Minjie would like to particularly thank Dusan Drabik for his valuable suggestions on one of the draft versions of this paper, and Frederic Ang and Ana Kujundzic for their comments on the 2021 WASS PhD Day seminar at Wageningen University & Research.

* Corresponding author at: Nanjing Agricultural University, Weigang No.1, Xuanwu District, Nanjing, Jiangsu Province 210095, China.
E-mail address: shuyifeng@njau.edu.cn (S. Feng).

https://doi.org/10.1016/j.foodpol.2022.102350
Received 28 September 2021; Received in revised form 22 August 2022; Accepted 26 August 2022
Available online 6 September 2022

two reasons: first, equal land distribution contributes to land misallocation between farms because farms are usually heterogeneous in their land productivities; and second, small farm sizes may contribute to capital misallocation between farms because small farms face relatively large barriers to capital markets (Adamopoulos et al., 2020).

Recent empirical evidence at the national level for China supports these implications. Adamopoulos et al. (2020), Gai et al. (2020), Zhao (2020) and Chari et al. (2021) find 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. 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 in China. 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 available literature has mostly neglected 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., 2016a; Wang et al., 2016b; Sheng et al., 2017; Zhang 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 hired machinery services can affect the demand for agricultural land on farms and generate an equilibrium distribution (or 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 (see, for example, 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 for all farms. This method is applied even though the farms are in different agroclimatic zones and use fundamentally different cropping systems that are likely to be characterised by significantly different factor output elasticities.

Based on these considerations, this paper 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 survey data set collected from four counties in Hebei Province, China. These counties are located within the North China Plain, 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 North China Plain. Operational farm sizes in the region are usually extremely small; our data set indicates that approximately 93% of surveyed farming households operate a farm size less than one hectare in 2017. Given this situation, the conventional wisdom may lead one to conclude that there is large factor misallocation across farms of the region. Nonetheless, we also observe 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 and 4).

We construct a quantitative framework that links micro-level productivities of heterogeneous farms to macro-level outcomes to assess the extent of factor misallocation in our study area (Adamopoulos and Restuccia, 2014; Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Ayerst et al., 2020; Chen et al., 2020). We use a non-parametric approach to estimate the distribution of farm-level TFPs for a set of farms specializing in wheat-maize double-cropping, controlling for potentially confounding factors such as farm-level irrigation conditions, soil quality and village fixed effects. We find that the measured dispersions in the distribution of farm-level productivities are small, implying that the misallocation of land and capital may be small as well under the current distribution of farm sizes. A quantification of the potential gains in aggregate agricultural output and productivity from efficient land and capital reallocations within the region confirms that factor misallocation is indeed moderate: the estimated output (productivity) gains in the region range from approximately 7% for within-village reallocation to 10% for between-village reallocation.

Although a direct comparison of our findings with those in the literature should be cautious due to differences of data coverage in space and time, our study robustly suggests 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; Gai et al., 2020; Chari et al., 2021). We argue that the major contribution to this lower-than-expected factor misallocation comes from the active use of hired machinery services among smallholders. Our finding may have important implications for public policies involving land and agricultural productivities not only in the local region and the larger North China Plain that shares similar production patterns, but also in other developing countries where smallholder production and factor misallocation persist.

The rest of the paper is structured as follows. Section 2 specifies a quantitative framework that explains how factor misallocation can be assessed. We describe the study area and survey data set in Sections 3 and 4, respectively. Section 5 estimates and discusses the potential misallocation of land and capital for the surveyed households in the study area. We draw conclusions and lay out the policy implications in Section 6.

2. Quantitative framework

In this section, we set up a quantitative framework to assess to what extent productive factors are misallocated *across* farms. Following the approach proposed by, for instance, 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, farming capital K, and a finite number of farms M indexed by i. A farm is a production unit that is managed by an operator who uses farming skills and production factors that are under his or her control to produce agricultural goods. Farm operators are assumed to be heterogeneous in their ability s_i in managing their farms. Farm-level production function features a 'span of control' (see Lucas, 1978) that is characterized by constant returns to scale for production technology and diminishing returns to scale for managerial skill:

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

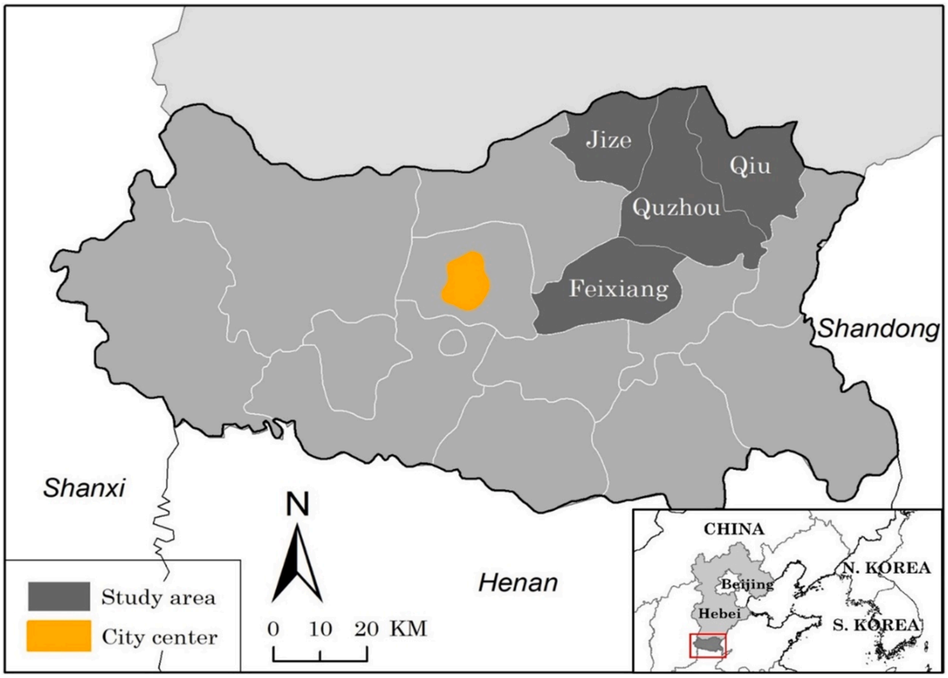

Fig. 1. Location of the study area in Handan Prefecture, Hebei Province, China.

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, Eq. (1) abstracts away from labor input differences across farms. We return to this abstraction and discuss its validity in Section 5.1.

We assume that a social planner of the rural economy decides how to allocate land and capital across farms to maximize aggregate output $Y = \sum_i y_i$, given farm-level production technologies in Eq. (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 across farms as follows:

$$l_i^e = \frac{s_i}{\sum_{i=1}^M s_i} L; k_i^e = \frac{s_i}{\sum_{i=1}^M s_i} K; \tag{2}$$

where the superscript e represents the efficient allocation of each input. Eq. (2) implies that, in the static equilibrium, the social planner allocates land and capital according to farms' *relative* farming abilities $(s_i / \sum_{i=1}^M s_i)$ 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, Eq. (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 Eq. (2) into $Y = \sum_i y_i$ to derive the aggregate production function under efficient resource allocation. This gives,

$$Y^e = TFP^e \cdot M^{1-\gamma} \left(L^\alpha K^{1-\alpha}\right)^\gamma \tag{3}$$

where Y^e is the aggregate output level under efficient factor allocation; $TFP^e = (\overline{S})^{1-\gamma}$ measures aggregate productivity in the economy, and $\overline{S} = M^{-1} \sum_{i=1}^M s_i$ is the average farming ability of the M farms. The potential gain in aggregate output can then be quantified by comparing this efficient aggregate output to 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. In the following sections, we apply this quantitative framework to farm-level data collected from a region in the North China Plain.

3. 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 Fig. 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 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 that is known as the "bread basket" of China and extends across provinces including Hebei, Henan, Shandong,

Table 1
Sample distribution of 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%.

Table 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.

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).

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 and 50 m) and land slope; annual average temperatures in 2016 and 2017 of these four counties are around 14 ~ 15 ℃. 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 and physically suitable for large scale agricultural production, most farms are extremely small. The average operational farm sizes 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 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 specialised machinery services providers, usually local third-party machine owners (e.g., other farms or farm cooperatives). Large farms may hire machinery services from outside the area or rely on their own machinery.

The relatively homogenous agro-ecological environment, predominance of the wheat-maize double-cropping system, very small farm sizes, and the extensive use of hired machinery services make the study region well-suited for reaching the aim of our study. In fact, given that wheat-maize double-cropping is the main cropping system in a large part of the North China Plain, and that smallholder farming with increased use of machinery services characterises those regions as well, our findings are likely to be relevant for a much larger region.

4. 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 research project that studies farm size enlargement and its implications. In sampling, we first selected 28 townships out of 33 in four counties; five townships were excluded because one was mainly composed of minority ethnic population and the other four were county centres 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. 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). Using information collected during pre-survey field trips, villages that specialized in cash crops such as vegetables, cotton and grapes were excluded (see Qian et al., 2020). This procedure gave us 135 villages with wheat-maize production as the dominating cropping system. 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. Out 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 the static factor allocation among existing farms, we first dropped 89 households that did not cultivate land in that season. We then also dropped 112 households that did not produce either wheat, or maize, or both, and 128 households that reported different (non-zero) sown areas for wheat and for maize. We focused our analysis on wheat-maize double-cropping farmers, because including the production of other agricultural products (e.g., vegetables and cotton) can lead to reduced accuracy in measuring farm-level productivities as these crops are usually grown using significantly different production technologies. The survey therefore did not collect input–output information for other crops than wheat and maize. The resulting sample includes 1,788 households that mostly specialize in wheat-maize double-cropping.[1] 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 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 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.

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 12.7% of the full sample of 2,121 households reported land rent-in and 15.2% reported

[1] This number of households comes from dropping another four wheat-maize double-cropping households due to negative value added (see Section 5 and Appendix A for details).

land rent-out in 2017.[2] As a comparison, the percentage of rural households reporting land rent-out for the whole country equalled 30% in 2016 (MOA, 2017).

Hired machinery services are very common especially in the production stages of land preparation, seeding, and harvesting (see Table 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 the total labor input in wheat and maize production.

5. Empirical application

To apply the quantitative framework in Section 2 to data, we construct farm-level total factor productivity (TFP) residually from farm i's production function in Eq. (1):

$$TFP_i \equiv s_i^{1-\gamma} = \frac{y_i}{\left(l_i^{\alpha} k_i^{1-\alpha}\right)^{\gamma}} \tag{4}$$

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

5.1. Measuring farm-level productivity and productivity dispersions

We use the data set described in Section 4 to construct farm-level output y_i, land input l_i and capital input k_i in Eq. (4). In particular, farm output is measured by "real" value-added that subtracts "real" costs of intermediate inputs from the "real" gross output of wheat and maize. Land input is measured by the operational land size devoted to wheat-maize double-cropping, rather than the double-counted sown areas for wheat and maize. For this reason, it is necessary to exclude farms that reported different sown areas for wheat and maize production.[3] A key difference between this study and the previous literature (e.g., Adamopoulos et al., 2020) is the measure of capital input: we rely heavily on the cost of hired machinery services to measure capital input, while also adding in the imputed cost of using own machine and small agricultural tools. 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 Eq. (1) (and therefore also the farm-level TFP in Eq. (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 (e.g., Restuccia and Santaeulàlia-Llopis, 2017; Adamopoulos et al., 2020; Chen et al., 2020), we normalize y_i, l_i and k_i and express them in unit labor input. Such a construction implies that we ignore the potential misallocation of labor across farms, and therefore the estimated misallocation could be conservative if labor misallocation were huge. Fortunately, 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 4) that cannot be effectively reallocated across farms in practice (see Chen et al., 2020).

Measuring farm-level TFPs also requires information on the parameters α and γ, which are related to factor output elasticities. While there are several approaches to measure them, we follow the convention in the literature of between-farm factor misallocation and directly compute them from the available data.[4] The capital income share for each farm is computed as the ratio of the 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 4), 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/year (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 Table B.1 of 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 Eq. (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 overestimate its farm-level TFP. To address this concern, we follow Adamopoulos et al. (2020) and further estimate the physical component of farm-level productivity by regressing (without a constant) the foregoing log farm-level TFPs on a set of potentially confounding factors. In particular, we include farm-level irrigation condition, soil type (as an indicator of soil quality), and village-level fixed effects, and specify the model as follows:

$$\ln TFP_{iv} = \beta_1 \times irrigation_{iv} + \beta_2 \times soil\_type_{iv} + \sum_v \delta_v \times village_v + \epsilon_{iv} \tag{5}$$

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). "$soil\_type_{iv}$" 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. Farm-level irrigation condition is included because local crop production relies heavily on irrigation, and better irrigation condition also copes better with weather risk (see more discussions in Section 3). Farm-specific soil quality is usually also an important factor that affects farm productivity; it is included in the model despite the

[2] We conducted the field survey right after the Chinese lunar new year, when most family members were at home, to avoid large replacements in random sampling. But households with contracted land in the study area who rented out their land and have permanently migrated to urban areas could not be interviewed. As a result, the land rent-out percentage in our sample may be slightly underestimated.

[3] Table B.4 in Appendix B reports the results that are obtained when farms that reported different (non-zero) sown areas for wheat and maize production are also included.

[4] In addition to the non-parametric approach that we adopt here, these parameters can also be obtained by estimating an average production function using ordinary least squares or other methods if the endogeneity issue of input choices is well taken care of (see Syverson, 2011), or by estimating a stochastic frontier production function if within-farm efficiency levels are a major concern (see Coelli et al., 2005).

Table 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 6 for definition).

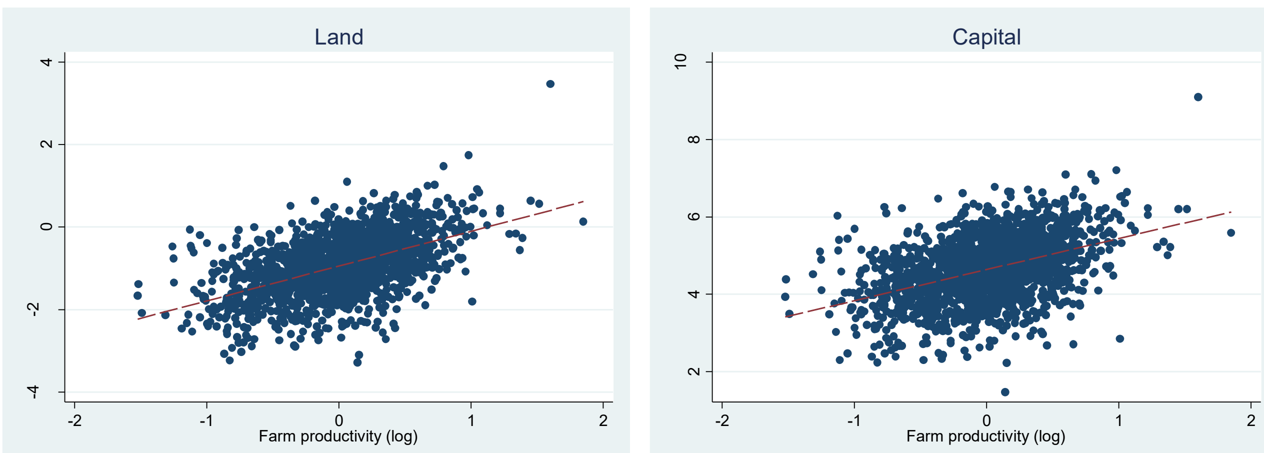

Fig. 2. Land and capital allocation across farms with different productivities.

Table 4
Aggregate output (productivity) 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.
Notes: Gains are based on the trimmed sample of 1,772 farms.

study area is relatively homogeneous in agro-environment (see also in Section 3). In Table B.2 of Appendix B, we show that dropping this variable does not significantly affect our measured dispersions of farm level TFPs. Due to data limitations, we do not include farm-level or village-level land quality information in the estimation. Nevertheless, there are two reasons that may justify the exclusion of land quality in our study area. First, the local area is a fluvial plain with minimal variations in key land quality components such as elevation, slope, terrain, and erosion (see details in Section 3). Second, land quality differences are generally taken into account by village leaders when determining the allocation of farmland use rights based on the principle of equality to households in their villages (Qu et al., 1995). Village fixed effects are included to account for other unobserved village-specific effects such as external technology interventions;[5] they are also inclusive of township- or county-specific effects. We use the regression residual from Eq. (5) to measure the (log) physical productivity at the farm level, which is,

$$\ln\widehat{TFP}_{iv} = \ln TFP_{iv} - \widehat{\beta_1} \times irrigation_{iv} - \widehat{\beta_2} \times soil\_type_{iv} - \sum_{v}\widehat{\delta_v} \times village_v \tag{6}$$

Columns (1) and (2) in Table 3 summarize 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.[6] As expected, the standard deviation and the log TFP difference between the 99th and 1st percentile

[5] 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).

[6] 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 comes from one single village in Quzhou County.

Table B1
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)
Factor 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 6 for definition) were dropped.

Table B2
Dispersions of farm-level TFPs by excluding farm-level soil types in estimation.

	(1) Soil type is excluded from Eq. (5) (Full sample)	(2) Soil type is excluded from Eq. (5) (15 extreme values excluded)
Country	China	China
Data coverage	Regional	Regional
Data period	2016/2017	2016/2017
Std. Dev.	0.59	0.43
p75-p25	0.56	0.56
p90-p10	1.10	1.10
p95-p5	1.41	1.39
p99-p1	2.51	2.01
N	1,788	1,773

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 15 extreme values (see footnote 6 in the main text for definition).

farms reduced significantly after deleting these extreme values, while the other dispersion measures are fairly robust.

To illustrate the consequences of estimating farm productivities for a relatively homogenous region, we compare the magnitudes of the regional productivity dispersions obtained in our study (columns (1) and (2) in Table 3) with the productivity dispersion measures obtained by Adamopoulos et al. (2020) for farms in China during the period of 1993–2002 and by Restuccia and Santaeulàlia-Llopis (2017) for farms in Malawi in the 2010/2011 season (columns (3) and (4) in Table 3). As can be seen from the table, the values of the dispersion measures in those two nationwide studies are more than twice the values that we obtained for our study region. Our measured dispersions are closer to those found by Ayerst et al. (2020) for China’s neighbouring country Vietnam during 2012–2016 (column (5) in Table 3), which has a system of rural land allocation in the north that resembles the Chinese system. Note that, however, direct comparison with others should be done with caution, as the estimated gaps may be driven by differences in data coverage in time and space, and by the inclusion of machinery services in the capital measure in our study. We discuss this important issue in Section 5.3.

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 2. We first visually contrast the distribution of observed factor inputs to the distribution of measured farm-level TFPs, and then we quantify the static gains in aggregate output (or productivity) from efficient resource allocation.

To start, note that Eq. (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 or 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. Fig. 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 Eq. (3) and measure the gain as the percentage change between efficient aggregate output level to the actual aggregate output level (see, for example, Restuccia and Santaeulàlia-Llopis, 2017; Chen et al., 2020):

$$AggregateGains = \frac{Y^e - Y^a}{Y^a} = \frac{Y^e}{\sum_i y_i^a} - 1 \tag{7}$$

where Y^e denotes the efficient aggregate output level when factors are efficiently allocated across farms according to Eq. (2); Y^a is the actual aggregate output level observed in the data set. To make them comparable, we use the 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 Eq. (7) also implies the percentage gain in aggregate productivity.

Table 4 presents the results from 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 Fig. 2. They are much smaller than the gains estimated by other studies for China. For example, in Adamopoulos et al. (2020), the estimated gains equal to 24.4% for within-village reallocation and 53.2% for within- and between-villages reallocation. Chari et al. (2021) focus on the period between 2003 and 2010 and perform an exercise similar to Adamopoulos et al. (2020) and find that if all misallocation of

Table B3
Farm-level TFP dispersions and aggregate output (productivity) gains with alternative formations of capital input.

	(1) Own machine cost = hired machinery cost (per unit land, results in the main text)	(2) Own machine cost = 150% of hired machinery cost (per unit land)	(3) Own machine cost = 50% of hired machinery cost (per unit land)	(4) Excluding households not using machines
Factor income shares				
Capital income share	0.205	0.213	0.196	0.207
Land income share	0.318	0.318	0.318	0.318
Labor income share	0.477	0.469	0.486	0.475
Farm-level TFP dispersions				
Std. Dev.	0.44	0.44	0.44	0.44
p75-p25	0.56	0.55	0.56	0.56
p90-p10	1.12	1.11	1.13	1.13
p95-p5	1.43	1.44	1.45	1.45
p99-p1	2.06	2.07	2.09	2.09
Correlation coefficients				
Corr (log land input, log TFP)	0.52	0.52	0.52	0.52
Corr (log capital input, log TFP)	0.43	0.41	0.44	0.43
Eliminating land and capital misallocation across households				
within villages	7.03%	7.34%	6.97%	7.12%
within and across villages	9.87%	10.34%	9.75%	10.06%
N	1,772	1,772	1,772	1,730

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 6 for definition) were dropped.

Table B4
Farm-level TFP dispersions and aggregate output (productivity) gains with extended sample.

	(1) Excluding 128 households that reported different sown areas for wheat and maize (Results in the main text)	(2) Including 128 households that reported different sown areas for wheat and maize
Factor income shares		
Capital income share	0.205	0.204
Land income share	0.318	0.319
Labor income share	0.477	0.477
Farm-level TFP dispersions		
Std. Dev.	0.44	0.44
p75-p25	0.56	0.56
p90-p10	1.12	1.12
p95-p5	1.43	1.43
p99-p1	2.06	2.08
Correlation coefficients		
Corr (log land input, log TFP)	0.52	0.53
Corr (log capital input, log TFP)	0.43	0.43
Eliminating land and capital misallocation across households		
within villages	7.03%	6.84%
within and across villages	9.87%	9.55%
N	1,772	1,900

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 6 for definition) were dropped.

land were eliminated, aggregate output in China during that period of time would increase by 73%. Again, we note that comparison across these studies should be cautious and may be even misleading given the differences in data coverage, time range, 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 output and productivity gains from factor reallocation are much lower than one would expect from the literature.

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 machinery 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 (Adamopoulos and Restuccia, 2014; Chen et al., 2020; Le, 2020). 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 (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 4). 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 among existing farms 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 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 Eq. (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 (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.[7] It may also facilitate the convergence of productivities among farms of different sizes by diffusing the frontier production technologies typically 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 factor misallocation is due to the inclusion of hired machinery services in capital measure, 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 right-hand side of Eq. (1) is measured by the flow cost of capital services generated from the measured 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 5.1 and 5.2. However, due to data limitations on capital stock measures,[8] we leave this important question for future studies.

6. Conclusion and policy implication

In this paper, 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, given the small and relatively equally distributed farm sizes in the study area. Our finding suggests that improving local agricultural output and productivity through 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.

This finding can have important policy implications. Land market imperfections can lead to significant losses in aggregate agricultural output, and thereby contribute to food insecurity. Reallocating land to the most productive farmers as a way to stimulate total agricultural output often faces great social and political challenges, as farmland may also play an important risk-reducing role by providing food security and social safety nets to smallholders. Our finding indicates that fostering efficiencies in the allocation of productive factors such as capital, can be a suitable alternative if land reforms are costly and land rental markets are underdeveloped. In particular, we showed that promoting the use of hired machinery services among smallholders contributes to the equalization of capital-land ratios, and thereby reduces the extent of factor misallocation and improves aggregate agricultural output and productivity. In this way, both the access to and the availability of food can be promoted, as is the case with the smallholders living in the study area in the North China Plain – also known as the 'bread basket' of China – examined for this study.

Our finding may be considered as an echo of the recent discussions in Fuglie et al. (2019) 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 (Vollrath, 2007). It is consistent with Schultz' (1964) proposition that smallholder farmers are poor but efficient, and they rationally respond to innovations (see also in Blank, 2008). Moreover, it can also be consistent with the recent findings in Cusolito and Maloney (2018), who analysed 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%.

Our study is not free of limitations. We particularly discuss two of them here. First, to accurately measure farm-level TFPs, we have mainly focused on wheat-maize double-cropping farms in the sample. However, these farms may also use part of their land to grow other crops or leave the land fallow. The survey did not collect information on those other land uses. The impact of excluding those land uses is likely to be small because on average more than 88% of operational farmland was used for wheat-maize double-cropping in the sample (see Section 4). Future studies may check the robustness of our findings by including also other farm activities in the analysis. Focusing on wheat-maize double-cropping also means that we excluded farms that did not produce wheat and/or maize, or that reported different (non-zero) sown areas for wheat and maize. The results presented in Table B4 in Appendix B show that including the 128 farms with different (non-zero) sown areas gives very similar results. But the impact of excluding the 112 farms that did not produce wheat and/or maize is unknown.

Second, a key assumption in estimating the productivity gains is that total resource endowments, i.e., land, capital, and the number of farms, remain fixed. For a regional study of static resource allocation, 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 (Yang et al., 2013; Zhang et al.,

[7] However, on the other hand, Chari et al. (2021) 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.

[8] 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 how much money they could earn if they sold the machines on the market. Other than these, the survey did not collect information of fixed assets such as grain storage facilities, means of transportation or machinery housing. However, our field experience indicates that very few households possess these fixed assets. Three possible reasons may explain this phenomenon: First, crop outputs are usually sold immediately after harvesting with buyers providing means of transportation and no need for farmers to store output. Second, 73% of the interviewed households reported no possession of agricultural machines, and hence did not need machinery housing. Third, the value of agricultural tools is usually small and many households chose not to value and report them during the survey.

2017). The assumption of fixed total capital endowment in the region may no longer hold when the share of machinery services coming from outside the region is non-negligible. Our data set contains no 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. The static nature of the current study also implies that the assumption of fixed capital and labor endowment no longer holds when a dynamic angle is adopted in which external capital and relatively efficient producers (such as agribusiness firms) can enter the agricultural sector while less productive farms exit. In such a process, a well-functioning land rental market that secures land tenure rights may be more important than the mass adoption of hired machinery services as the former may significantly encourage farm entry and exit through cross-sectoral resource reallocation and incentivize long-term agricultural investments.[9] We leave this for future research.

CRediT authorship contribution statement

Minjie Chen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Nico Heerink:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Xueqin Zhu:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Shuyi Feng:** Writing – review & editing, Investigation, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Financial support for this research was granted by the National Key R&D Program of China [grant number 2016YFE0103100], and the Programme Strategic Scientific Alliances (PSA) of the Royal Netherlands Academy of Arts and Sciences (KNAW) and the Ministry of Science and Technology, China [grant number PSA-SA-E-01] (SURE + project).

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 1,947 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; Adomopoulos et al., 2020; Chen et al., 2020). In this paper, 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 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.[10]

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 products with different qualities. For example, different types of compound fertilizer are used in our study area, but farmers can hardly recall the fertilizer type that they bought.[11] The problem is most eminent for agrochemicals, due to the great diversity of products that are used and their 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 Eq. (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. It is the operational land size used for wheat-maize double-cropping, rather than the double-counted sown areas for wheat and maize. 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 hired machinery services plus the imputed flow costs of using own machines and small agricultural tools. The data set contains detailed information on the cost of hired machinery services per unit of land. We assume that the variation in these costs reflects real cost differences due to farm location, land fragmentation, and other physical differences in production. For farmers using own machinery, we use the within-village average rental rate of hired machinery services as a proxy of the flow cost of the use of own machinery per unit land. There are a few households in the sample that did not use machines at all in wheat and maize production, and

[9] For the former, however, 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.

[10] Observed output price variations in our data set 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 NBS-DRS, 2019).

[11] 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 accounting for 20%, 15%, and 10%. These two are usually priced differently and should be taken as different fertilizer types.

hence may use small agricultural tools. For these households, we use the average of the lowest 10% values in the sample distribution of hired machinery services costs per unit land as a proxy of the flow cost of using small agricultural tools. Its value equals 89 yuan/mu. Using alternative proxies of the flow cost of the use of own machinery or dropping farms not using any machines does not significantly change our main results (see Table B3 in Appendix B).

Appendix B. Robustness checks

Alternative factor income shares

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 B1 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). 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 B1, 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 B1 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.

Excluding soil quality

Usually, farm-specific soil quality affects farm productivity. In the main text, we include it in the model despite our study area is relatively homogeneous in agro-environment (see Section 3). Here we drop it and re-estimated Eqs. (5) and (6) to check the robustness of our measured dispersions of farm level TFPs in Table 3. The estimation results are presented below in Table B.2. These dispersion measures are virtually very similar to those we have obtained in columns (1) and (2) in Table 3, indicating that excluding soil type from Eq. (5) indeed does not significantly change our findings.

Alternative formations of capital input

In the main analysis, we use the within-village average rental rate of hired machinery services per unit land as a proxy of the flow cost of own machines per unit land; we also use the average of the lowest 10% values in the sample distribution of hired machinery services costs per unit land as a proxy of the flow cost of using small agricultural tools for farmers not using machines (see Appendix A). In this part, we perform a set of sensitivity analyses to check if our main results are sensitive to these specific formations of capital input. First, we set the flow cost of using own machinery per unit land to be equivalent to 150% and 50%, respectively, of the within-village average rental rate of hired machinery services. Second, we exclude farms not using any hired or own machines. The resulting TFP dispersions and productivity gains are reported in Table B3. Compared to the main results presented in column (1), we find that using alternative measures of own machinery input (columns (2) and (3)) or dropping farms that do not use machines from the sample (column (4)) has a very minor impact on the main results.

Extending sample size

In this part we test if our TFP dispersion measures and the subsequent assessment of factor misallocation are sensitive to the inclusion of 128 households that reported different (non-zero) sown areas for wheat and maize production. The results are reported in Table B4. Again, column (1) of Table B4 replicates our results in the main text, i.e., without the 128 households. In column (2), the 128 households are included, and the estimates are obtained by loosely measuring land input as the average sown area of wheat and maize on each farm (this operation is much less reliable for the 112 households that did not produce either wheat, or maize, or both). A comparison between these two columns indicates that inclusion or exclusion of these 128 households give virtually very similar results.

References

Adamopoulos, T., Brandt, L., Leight, J., Restuccia, D., 2020. Misallocation, selection and productivity: a quantitative analysis with panel data from China. NBER working paper No. w23039. https://doi.org/10.3386/w23039.

Adamopoulos, T., Restuccia, D., 2014. The size distribution of farms and international productivity differences. Am. Econ. Rev. 104 (6), 1667–1697.

Ayerst, S., Brandt, L., Restuccia, D., 2020. Market constraints, misallocation, and productivity in Vietnam agriculture. Food Policy 101840.

Bartelsman, E.J., Doms, M., 2000. Understanding productivity: lessons from longitudinal microdata. J. Econ. Literature 38 (3), 569–594.

Benjamin, D., Brandt, L., Giles, J., 2005. The evolution of income inequality in rural China. Econ. Dev. Cult. Change 53 (4), 769–824. https://doi.org/10.1086/428713.

Blank, S.C., 2008. The Economics of American Agriculture: Evolution and Global Development. Armonk. M.E. Sharpe Inc., New York, U.S.A.

Brandt, L., Huang, J., Li, G., Rozelle, S., 2002. Land rights in rural china: facts, fictions and issues. China J. 47, 67–97.

Cao, K.H., Birchenall, J.A., 2013. Agricultural productivity, structural change, and economic growth in post-reform China. J. Dev. Econ. 104, 165–180. https://doi.org/10.1016/j.jdeveco.2013.06.001.

Chari, A., Liu, E.M., Wang, S.-Y., Wang, Y., 2021. Property rights, land misallocation and agricultural efficiency in China. Rev. Econ. Stud. 88 (4), 1831–1862. https://doi.org/10.1093/restud/rdaa072.

Chen, C., Restuccia, D., Santaeulàlia-Llopis, R., 2020. The effects of land markets on resource allocation and agricultural productivity. NBER working paper No. w24034. https://doi.org/10.3386/w24034.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis, 2nd edition. Springer Science & Business Media.

Cusolito, A.P., Maloney, W.F., 2018. Productivity revisited: Shifting paradigms in analysis and policy. The World Bank, Washington, DC.

Foster, L., Haltiwanger, J., Syverson, C., 2008. Reallocation, firm turnover, and efficiency: selection on productivity or profitability? Am. Econ. Rev. 98 (1), 394–425. https://doi.org/10.1257/aer.98.1.394.

Fuglie, K., Gautam, M., Goyal, A., Maloney, W.F., 2019. Harvesting Prosperity: Technology and Productivity Growth in Agriculture. World Bank, Washington, DC.

Gai, Q., Cheng, M., Zhu, X., Shi, Q., 2020. Can land rent improve land allocation's efficiency? Evidence from National Fixed Point Survey. China Econ. Quart. 20 (1), 321–340 in Chinese.

Gollin, D., Udry, C., 2021. Heterogeneity, measurement error, and misallocation: evidence from African agriculture. J. Political Econ. 129 (1), 1–80. https://doi.org/10.1086/711369.

Gong, B., 2018. Agricultural reforms and production in China: changes in provincial production function and productivity in 1978–2015. J. Dev. Econ. 132 (October 2017), 18–31.

Handan Bureau of Statistics (HBS), 2017. Handan Yearbook of Statistics 2017. Beijing: China Statistics Press. (in Chinese).

Handan Bureau of Statistics (HBS), 2018. Handan Yearbook of Statistics 2018. Beijing: China Statistics Press. (in Chinese).

Handan Municipal Development and Reform Committee (HMDRC), 2018. Costs and revenues analyses report for major agricultural products in Handan 2017. Available in Chinese at: http://www.hd.gov.cn/fgw/xwzx/tzgg/201802/t20180201_762812.html.

Hsieh, C.-T., Klenow, P.J., 2009. Misallocation and manufacturing TFP in China and India. Quart. J. Econ. 124 (4), 1403–1448.

Ivanic, M., Martin, W., 2018. Sectoral productivity growth and poverty reduction: national and global impacts. World Dev. 109, 429–439.

Le, K., 2020. Land use restrictions, misallocation in agriculture, and aggregate productivity in Vietnam. J. Dev. Econ. 145 (March), 102465. https://doi.org/10.1016/j.jdeveco.2020.102465.

Li, F., Li, D., Feng, S., Zhang, W., Heerink, N., 2020. Empowering smallholders for sustainable grain production: A case study of the science and technology backyard. In: Paper presented on 12th CAER-IFPRI annual conference: Urban-Rural Integrated Development in China: Challenges and Solutions. Chongqing, China.

Ligon, E., Sadoulet, E., 2018. Estimating the relative benefits of agricultural growth on the distribution of expenditures. World Dev. 109, 417–428.

Liu, Y., Heerink, N., Li, F., Shi, X., 2020. Do agricultural machinery services promote village land rental markets? Theory and evidence from the North China Plain. Manuscript. Wageningen University and Research.

Lucas Jr, R.E., 1978. On the size distribution of business firms. Bell J. Econ. 508–523.

Ministry of Agriculture and Rural Affairs of China (MOA), 2017. China Agricultural Development Report 2017. Beijing: China Agricultural Press (in Chinese).

National Bureau of Statistics (NBS), 2018. China Yearbook of Statistics 2018. Beijing: China Statistics Press. (in Chinese).

National Bureau of Statistics-Department of Rural Surveys (NBS-DRS), 2019. China Yearbook of Agricultural Price Survey 2019. Beijing: China Statistics Press. (in Chinese).
Qian, C., Li, F., Antonides, G., Heerink, N., Ma, X., Li, X., 2020. Effect of personality traits on smallholders' land renting behavior: theory and evidence from the North China Plain. China Econ. Rev. 101510.
Qu, F., Heerink, N., Wang, W., 1995. Land administration reform in China: its impact on land allocation and economic development. Land Use Policy 12, 193–203.
Ray, D., 1998. Development Economics. Princeton University Press, Princeton, New Jersey.
Restuccia, D., Rogerson, R., 2013. Misallocation and productivity. Rev. Econ. Dyn. 16 (1), 1–10. https://doi.org/10.1016/j.red.2012.11.003.
Restuccia, D., Rogerson, R., 2017. The causes and costs of misallocation. J. Econ. Perspectives 31 (3), 151–174. https://doi.org/10.1257/jep.31.3.151.
Restuccia, D., Santaeulàlia-Llopis, R., 2017. Land misallocation and productivityNBER Working Paper No. 23128. https://doi.org/10.3386/w23128.
Rozelle, S., Swinnen, J.F.M., 2004. Success and failure of reform: Insights from the transition of agriculture. J. Econ. Literature 42 (2), 404–456. https://doi.org/10.1257/0022051041409048.
Schultz, T.W., 1964. Transforming Traditional Agriculture. Yale University Press, New Haven.
Sheng, Y., Song, L., Yi, Q., 2017. Mechanisation outsourcing and agricultural productivity for small farms: Implications for rural land reform in China. In: Song, L., Garnaut, R., Cai, F., Johnston, L. (Eds.), China's New Sources of Economic Growth: Human Capital, Innovation and Technological Change. ANU Press, Acton, Australia.
Sheng, Y., Tian, X., Qiao, W., Peng, C., 2020. Measuring agricultural total factor productivity in China: pattern and drivers over the period of 1978–2016. Aust. J. Agric. Resour. Econ. 64 (1), 82–103.
Syverson, C., 2011. What determines productivity. J. Econ. Literature 49 (2), 326–365.
Tybout, J.R., 2000. Manufacturing firms in developing countries: how well do they do, and why? J. Econ. Literature 38 (1), 11–44. https://doi.org/10.1257/jel.38.1.11.
Vollrath, D., 2007. Land distribution and international agricultural productivity. Am. J. Agric. Econ. 89 (1), 202–216.
Wang, X., Yamauchi, F., Huang, J., 2016a. Rising wages, mechanization, and the substitution between capital and labor: evidence from small scale farm system in China. Agric. Econ. 47 (3), 309–317.
Wang, X., Yamauchi, F., Otsuka, K., Huang, J., 2016b. Wage growth, landholding, and mechanization in Chinese agriculture. World Dev. 86, 30–45. https://doi.org/10.1016/j.worlddev.2016.05.002.
Wang, L., Yang, R., Wu, B., 2020. A study on total factor productivity of agricultural production of rural households in China. Manage. World 2020 (12), 77–93 in Chinese.
Yang, J., Huang, Z., Zhang, X., Reardon, T., 2013. The rapid rise of cross-regional agricultural mechanization services in China. Am. J. Agric. Econ. 95 (5), 1245–1251. https://doi.org/10.1093/ajae/aat027.
Zhang, X., Yang, J., Thomas, R., 2017. Mechanization outsourcing clusters and division of labor in Chinese agriculture. China Econ. Rev. 43, 184–195. https://doi.org/10.1016/j.chieco.2017.01.012.
Zhao, X., 2020. Land and labor allocation under communal tenure: theory and evidence from China. J. Dev. Econ. 147 https://doi.org/10.1016/j.jdeveco.2020.102526.
Zhu, X., Shi, Q., Gai, Q., 2011. Misallocation and TFP in rural China. Econ. Res. J. 2011 (5), 86–98 in Chinese.