Do small farm sizes imply large resource misallocation? Evidence from wheat-maize double-cropping farms in the North China Plain

by Minjie Chen, Nico Heerink, Xueqin Zhu, and Shuyi Feng

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Abstract

The egalitarian allocation of agricultural land and small 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 empirically examines to what extent land and capital are misallocated in a region of China that is characterized by small and relatively equally distributed farm sizes. Using a survey dataset 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 percent for within-village reallocation to 10 percent 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.

Keywords: resource misallocation, smallholders, machinery services, agricultural productivity

JEL codes: O11, O13, O47

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 largely been attributed to the growth in aggregate agricultural productivity (see Cao and Birchenall, 2013; Ivanic and Martin, 2018; Ligon and Sadoulet, 2018). Some recent studies, however, find that the growth rate of agricultural productivity (i.e. total factor productivity or TFP) is declining in recent years (e.g. Sheng et al., 2020; Gong, 2018). These findings cast doubt on China's potential for remaining food self-sufficient 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 provides support for 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 up 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 into the current situation of agricultural production. Moreover and interestingly, all these studies are based on the same nationally representative household-level panel dataset that was collected through the National Fixed Point Survey (see Benjamin et al., 2005 for a description), while evidence from alternative datasets is still missing. For these reasons, we identify two major gaps that still exist in this 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, largely 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 labour-intensive production towards 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. Moreover, the availability of hired machinery services may affect the demand for agricultural land on farms and generate an equilibrium distribution (allocation) of farm sizes that is different from what the literature suggested. 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 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, characterised by relatively equal distribution of land among smallholders and increased use of hired machinery services in crop production. Particularly, we exploit a household-level dataset 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. Average operational farm size in the region is extremely small while the use of hired machinery services is extremely high; our dataset 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 Section 2 and 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 Santaeulalia-Llopis, 2017; Adamopoulos et al., 2020; Ayerst et al., 2020; Chen et al., 2020). Fitting our data to this framework, we find that the measured dispersions in farm-level productivities are small, implying 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 paper is structured as follows. In Section 2, a background introduction of the study area is provided. We describe the survey dataset in Section 3. In Section 4, we specify a quantitative model to explain how we assess factor misallocation. Section 5 examines and discusses the potential misallocation of land and capital for the households in the survey dataset. We conclude in Section 7.

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 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 area in the prefecture. 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 a half of the national average. Primary industry GDP accounted for approximately 17% of total GDP within the area, twice as much as the remaining area in the prefecture and of the entire 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 middle 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).

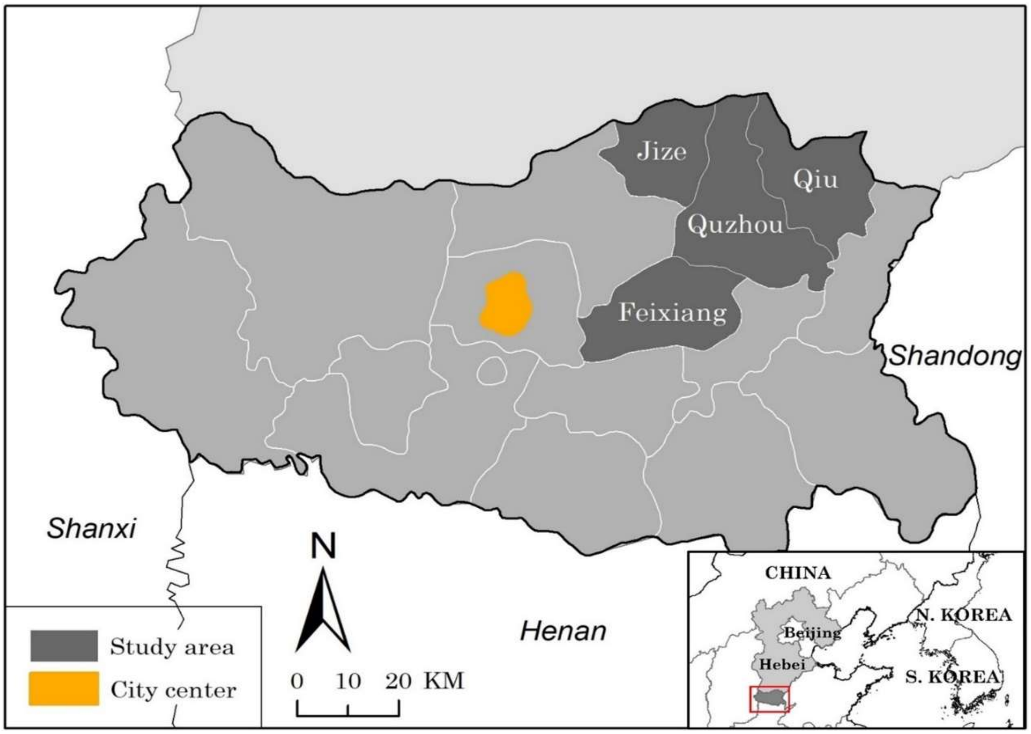


Figure 1. Location of the study area in Handan prefecture, Hebei Province, China

The agro-environmental characteristics for local crop production are relatively homogeneous. For example, the whole area locates 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 ℃. 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 rainfall concentrated in the summer. Crop production, particularly during the growing season of winter wheat, therefore, relies heavily on irrigation, using either surface water or ground water.

Although the area is relatively flat, most farms are extremely small. The average operational farm sizes in 2017 in these four counties varied between 5.8 - 9.5 mu (or equivalently 0.39 - 0.63 ha for 1 mu = 1/15 ha; HBS, 2018;). In recent years, labour-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 (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 machine services from outside of the area or rely on their own machinery.

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 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 village, 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 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. 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 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.[1] For them, we have not only detailed quantitative information of crop-specific input and output quantities and prices, but also qualitative information of 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 about 1% of the farms have a size larger 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 largest for relatively small farms.

Table 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

[1] Four wheat-maize double-cropping households are also dropped due to negative value added (see more discussion in Section 5 and Appendix 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%.[2] As a comparison, the percentage of farming households reported land rent-out for the whole country equalled 30% in 2016 (MOA, 2017).

Table 2. Share of households 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%	N/A	N/A
Seeding	92.17%	5.20%	90.27%	4.31%
Fertilization	6.94%	1.51%	10.46%	1.06%

[2] We particularly 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 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.

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, "N/A" in the table means that land preparation and seeding are preformed simultaneously with machine, and we record that only for seeding.

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, labour 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 production stages, family labor is the dominant form of labor input; it accounts for approximately 96% of the total labor input in wheat and maize production.

4. Quantitative framework

To empirically assess to what extent production factors are misallocated across these wheat-maize double-cropping farms, we closely follow Restuccia and Santaeulalia-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 that is 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. Farm-level production function features a 'span of control' (see Lucas, 1978) that has a constant returns to scale production technology and a diminishing returns to scale managerial skill:

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

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

The behavioural 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 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 as follows:

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

where the superscript e represents efficient allocation. Eq. (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) emphasizes 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 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,

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

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 to the actual aggregate output. If 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.

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 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, 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 Santaeulalia-Llopis, 2017; Adamopoulos et al., 2020; Gollin and Udry, 2021).

5.1. Measuring farm-level productivity and productivity dispersions

We use the dataset described in Section 3 to construct farm-level output y_i, land input l_i and capital input k_i in eq. (4). Particularly, 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 paper and previous literature is the measure of capital input. Particularly, 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 about the methods of variable construction.

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 dataset farms differ in their labor inputs. Following the convention in the literature (see Restuccia and Santaeulalia-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 ignored the potential misallocation of labor across farms, and therefore the estimated misallocation could be conservative if labor misallocation were huge. Nevertheless, 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) 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. The capital income share for each farm is computed 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 dataset contains only limited information on land rental prices due to the relatively small number of land rental transactions (see Section 3), and therefore, we use the average land rental price that was published by Handan municipal government one month right 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 Santaeulalia-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 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 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 condition because precipitation is relatively low in the study area and crop production heavily relies 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 2). This gives the following specification:

$$\ln TFP_{iv} = \beta_1 \times irrigation_{iv} + \beta_2 \times soil\_type_{iv} + \sum_{v} \delta_v \times village_v + \epsilon_{iv} \quad (5)$$

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 a categorical variable that measures three types of soil, i.e., sandy, clay and loam. The variable '$village_v$' represents village-fixed effects. β_1, β_2 and δ_v are the parameters to be estimated, 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.[3] We use the regression residuals from eq. (5) to measure the (log) physical productivity at the farm level, which is,

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

Column (1) and (2) in Table 3 summarizes several dispersion measures of this log farm-level TFPs. In column (1), which 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

[3] 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).

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.[4] 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. 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 Santaeulalia-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	---

[4] 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.

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

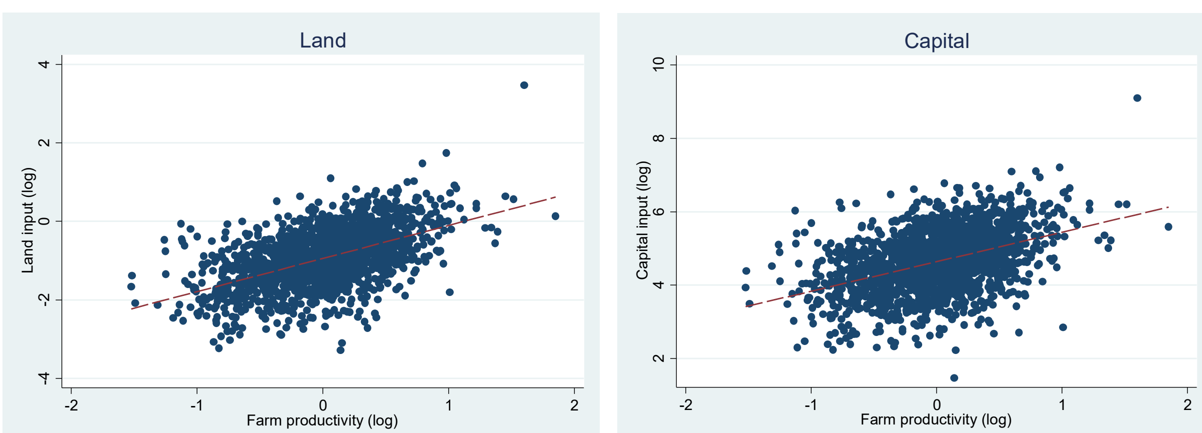
Notes: all dispersion measures are in logarithmic terms. 'Std. Dev.' is the standard deviation. 'p75-p25' is the difference between 75th and 25th percentiles in the distribution of log TFPs. Similar definition applies to other dispersion measures in the table. In column (2), we trimmed 16 extreme values (see footnote 4 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 Santaeulalia-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 standard deviation. Our measured dispersions are closer to those found by Ayerst et al. (2020) for China's neighbouring 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 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 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.

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 (land, capital) input 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 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). Put these in numbers, the correlation coefficients are 0.52 and 0.43 in the left and right panels, respectively. By contrast, Restuccia and Santaeulalia-Llopis (2017) find for Malawi that these correlation coefficients equal to 0.05 and -0.01, respectively; their findings imply little correlation and hence 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.



Notes: log farm productivity is estimated from eq. (6) and the data trimmed 16 extreme values (1,772 observations remain, see footnote 4). Land and capital are measured in labor-day terms. 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.

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

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 Santaeulalia-Llopis, 2017; Chen et al., 2020):

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

where Y^e denotes the aggregate output level when factors are efficiently allocated according to eq. (2); Y^a is the aggregate output level observed in the dataset. 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 imply the percentage gain in aggregate productivity.

Table 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 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 Figure 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 local operational farm sizes are extremely small and land rental market is mostly inactive, the estimated gains in aggregate output and productivity 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 held in a relatively small region with farms expected to be less heterogeneous in their productivities than in the case with nationwide analyses (that characterise most of the previous literature). However, this cannot be tested without a dataset that directly extents 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, in Le, 2020; Adamopoulos and Restuccia, 2014; Chen et al., 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 twenty 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). Nevertheless, land rental transactions are less common in our study area, despite the operational farm sizes are extremely small (see Section 3). Based on findings in the recent literature, these characteristics likely lead to conclusions that local land is severely misallocated and government's 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 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 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 (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.[5] 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 because of the inclusion of hired machinery services, two empirical approaches may 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 either the 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 eq. (1) is measured by capital stock. These updated measures of variables can then be applied to re-estimate factor income shares and farm-level

[5] However, in the other way around, 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.

TFPs, and to evaluate the extent of factor misallocation by following the same procedures in Section 5.1 and 5.2. However, due to data limitation on capital stock measures,[6] we leave this important question for future studies.

6. Conclusion

In this paper, we explored a farm-level dataset 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 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 a 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

[6] Our dataset 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 own 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.

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 to the recent discussions in Fuglie et al. (2019) that agricultural land may be not 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 also can 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%.[7]

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

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

agricultural land, this seems 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 capital endowment in the region no longer holds. Unfortunately, our dataset 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 further research.

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Appendix A: Measurement of farm-level output and inputs

Real value added. The dataset contains farm-specific information of wheat and maize output quantities (in kg) and farm-gate prices (in yuan/kg). The price information is missing for some farms and crops as no market transactions took place 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 Santaeulalia-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 dataset largely reflects 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.[8]

[8] 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).

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 their 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.[9] The problem is most eminent for agrochemicals, due to the great diversity of products that are used and their prices. Also, a narrowly defined study area may help reduce the possibility that cost variations are due to market conditions.

'Real' value added is computed by subtracting total intermediate inputs cost from the gross output value. This resulted in four negative values and we dropped them. Though negative values are allowed in the construction of eq. (4), dropping them would simplify our data analyses and interpretation while 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. Land area is measured by the cropland area planted with either wheat or maize in the 2016/2017 season. Labor input in the dataset is recorded in labor days. It 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.

[9] For fertilizer type, we mean the total and separate percentages of nutrients component (nitrogen, phosphate, potassium) in the compound fertilizer. For example, compound fertilizer may contain 45% of total nutrients, with N, P and K each accounts for 15%, 15% and 15% or 20%, 15% and 10%, and these two are priced differently and should be considered as different fertilizer types.

Capital input is measured by total expenditures on machine services. The dataset contains rich information on cost of hired machinery services per unit of land. The variation embedded in these unit costs, we argue, is a good reflection of real cost differences due to farm location, land fragmentation, and other physical differences of 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 not likely that a household uses machines (including both hired and own) only on the part of his sown area of wheat and maize while use labor on other parts. Still, there are 37 households that did not use machine 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 percent farms that reported to use machine, which is approximately 89 yuan/mu.[10] Robustness check by dropping these 37 observations shows that our results are not significantly affected by this imputation approach.

Appendix B: Robustness check with alternative factor income shares

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.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). 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 of 1993-2002 in China and are quite close to our own estimates. In column (3) of Table B.1, the income shares we use are 0.36 and 0.18

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

respectively for capital and land. These shares were adopted by Restuccia and Santaeulalia-Llopis (2017) to study Malawian agriculture. What Table B.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.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 Santaeulalia-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. '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 4 for definition) were dropped.