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# Resource Misallocation and Rice Productivity in Thailand

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ABSTRACT

Thailand's manufacturing sector is characterised by considerable resource misallocation compared with this sector in other countries, and the problem may extend to its agricultural sector as well. Using detailed household-level data on rice production from the 2013 Agricultural Census, this paper examines resource misallocation across farms in Thailand and its effect on the country's aggregate productivity in rice farming. I find that the marginal products of land and capital were largely dispersed, which is an indication of significant resource misallocation. I further estimate that reallocation of resources could increase aggregate output and productivity by approximately a factor of 1.67. This potential gain is not small, but it is smaller than that predicted in other studies for the Thai manufacturing sector and the Malawian agricultural sector, a result suggesting that the Thai rice farming sector is relatively less plagued by resource misallocation. Other developing countries may encounter similar degrees of misallocation in their agricultural sectors. I also find that an effective reallocation policy cannot involve simply reducing the landholdings of large landholders but rather supports high-productivity farmers to have more land and capital.

## INTRODUCTION

It is widely accepted that differences in income across countries are for the most part attributable to differences in productivity, and recent literature suggests that the misallocation of resources or factors of production plays an important role in this variation. Thus Restuccia and Rogerson (2008) showed that resource misallocation can lower a country's aggregate productivity by as much as 50%, and Hsieh and Klenow (2009) found high levels of resource misallocation in the Chinese and Indian manufacturing sectors and predicted that reallocation of resources could increase aggregate manufacturing productivity by 87-115% in China and 100-128% in India.

A number of studies have followed in the path of the pioneering empirical work by Hsieh and Klenow (2009). Bellone and Mallen-Pisano (2013) and Camacho and Conover (2010), for instance, found that the misallocation of resources in the manufacturing sectors of France and Colombia, respectively, was no more extensive than in the United States. On the other hand, Calligaris (2015), Ha et al. (2016), Ryzhenkov (2016), Neumeyer and Sandleris (2010), and Busso et al.

(2013) found that the manufacturing sectors of Italy, Vietnam, Ukraine, and several other Latin American countries, again respectively, were characterised by higher levels of resource misallocation than was the case in the United States. In the specific case of Thailand, Dheera-aumpon (2014) and Paweenawat et al. (2017) found that the manufacturing sector performed more poorly in terms of misallocation than in China, India, or the United States.

In some countries, the agricultural sector may likewise suffer from a resource misallocation problem. Thus Restuccia and Santaeulalia-Llopis (2017) in the study just mentioned reported severe resource misallocation of resources in the agricultural sector in Malawi and an associated adverse effect on aggregate output and productivity; by their calculations, reallocation of resources could increase aggregate agricultural output by as much as 260%. In Thailand, the agricultural sector may be compromised in like manner as the manufacturing sector. This study accordingly explores resource misallocation and its effect on aggregate productivity in the Thai agricultural sector.

The 2013 Agricultural Census conducted by the National Statistical Office of Thailand provides detailed household-level data both for inputs and for output relating to rice production. This paper applies the method used by Restuccia and Santaeulalia-Llopis (2017) in their study of Malawi to data relating to rice farmer households in Thailand in order to assess the extent of resource misallocation and its effect on the aggregate productivity of the country's rice farming industry. I find that the marginal products of land and capital are broadly dispersed across farmers, a situation that is indicative of extensive resource misallocation. According to my findings, efficient allocation of resources could increase the aggregate output and productivity of the Thai rice industry by approximately 67%. This gain is not small, though it is less than those estimated for the Thai manufacturing sector by Dheera-aumpon (2014) or for the Malawian agricultural sector by Restuccia and Santaeulalia-Llopis (2017). Thus Thai rice farming, while impeded by resource misallocation, is nevertheless more efficient in this regard than Thai manufacturing or the Malawian agriculture sector. Other developing countries outside Africa may find similar degrees of resource misallocation in their agricultural sectors.

In what follows, Section 2 describes the data used in the analysis and Section 3 the model and method used to derive the results, which are presented and discussed in Section 4. Section 5 describes robustness checks, Section 6 discusses the policy implications, and conclusions are offered in Section 7.

## 1. DATA

I used household-level data from Thailand's 2013 Agricultural Census, which was conducted by the National Statistical Office of Thailand. To be specific, the data set consisted of a sample of households based on the Census that was released by the National Statistical Office. The Census provides information on the characteristics of household-farms over a period of 12 months ending May 1, 2013. The original sample represented 62,984 households. The Census was relatively comprehensive in terms of the collection of the output of rice as compared with other crops produced by households, though only the data concerning the quantity of rice harvested by each was available. As a result, it was only possible to calculate the value of rice production. Omitting households in which no rice was produced, the sample was reduced to 38,850 rice-producing households.

I created from the Census data variables for the quantity of rice production (including both rice and sticky rice and both in- and off-season), the amount of chemical fertiliser used, the extent of land holding for rice cultivation, and the uses of agricultural equipment. To construct the value added, I subtracted the cost of chemical fertilisers, which was calculated using the average annual price from May 2012 to April 2013, from the value of rice production, which was calculated using the average price of paddy rice over the same period; the relevant information was obtained from the Office of Agricultural Economics. It is important to note that the information was available only for chemical fertilisers (i.e. not for such other intermediate inputs as herbicides, pesticides, and seeds) and that subtracting the common average cost of rice production from the value of rice production did not alter the results.

In terms of capital, the Census reports information on agricultural equipment, including both implements (such as sprayers, weeders, and planters) and machinery (such as tractors, motorised pumps, harvesters, and threshers). As a proxy for capital, I constructed an asset index for capital following the procedures of Filmer and Pritchett (2001), McKenzie (2005), and Restuccia and Santaeulalia-Llopis (2017). The index was based on dummy variables pertaining to the uses of agricultural equipment. I used a set of 17 relevant pieces of agricultural equipment from the Census to calculate a score from the first principal component.

To control for land quality, I constructed an index from data on physical appropriateness for rice cultivation obtained from the Land Development Department of the Ministry of Agriculture and Cooperatives. This index was based on the plots of land classified as particularly suitable for rice cultivation. To control for temporary output shocks, I used the total average rainfall in millimetres for 2012 and 2013. It must be observed that the National Statistical Office data only include the region in which a household is located and not the province or the district. The index of land quality and the total rainfall accordingly had to be assessed in terms of the weighted average over a given region based on the amount of land holding for rice cultivation.

After excluding households that did not provide information regarding chemical fertilisers and agricultural equipment, the sample consisted of 31,801 households.

## 2. METHOD

To assess resource misallocation across farms and its effect on the aggregate productivity of rice farming in Thailand, I used the method developed by Restuccia and Santaeulalia-Llopis (2017). To measure productivity at the farm level, I relied on the household-level data from the 2013 Agricultural Census as described in the previous section. Farm-level total factor productivity (TFP) $s_i$ was defined as the residual from the following farm-level production function:

$$y_i = s_i \zeta_i k_i^{\theta_k} \left(q_i l_i\right)^{\theta_l}, \quad \theta_k + \theta_l < 1,$$

where $y_i$ is the value added, $k_i$ is capital, $l_i$ is the amount of land holding for rice cultivation, $\zeta_i$ is a rain shock, $q_i$ is land quality, and $\theta_k$ and $\theta_l$ are the input elasticities. For comparability with other studies, I chose $\theta_k$ = 0.36 and $\theta_l$ = 0.18, again following Restuccia and Santaeulalia-Llopis (2017). To obtain the efficient allocation to serve as a benchmark, a planner was assumed to allocate capital and land across a given set of heterogeneous farmers whose productivity $s_i$ differed in order to maximise output given fixed total amounts of capital $K$ and land $L$. The benevolent social planner thus solved the following problem:

$$Y^e = \max_{\{k_i, l_i\}} \sum_i s_i k_i^{\theta_k} l_i^{\theta_l},$$

subject to

$$K = \sum_i k_i, \qquad L = \sum_i l_i.$$

Efficient allocation principally equates marginal products of capital and land across farmers, taking the following simple form:

$$k^e = \frac{z_i}{\sum_i z_i} K \, , \; l^e = \frac{z_i}{\sum_i z_i} L$$

where $z_i \equiv s_i^{1/(1-\theta_k-\theta_l)}$. To calculate the efficient allocation, I used farm-level productivity $s_i$ derived from the farm-level TFP calculated previously and the total amounts of capital and land from the data. To quantify the effect of resource misallocation on aggregate productivity, I calculated the output gain, defined as the ratio of efficient aggregate output to actual aggregate output:

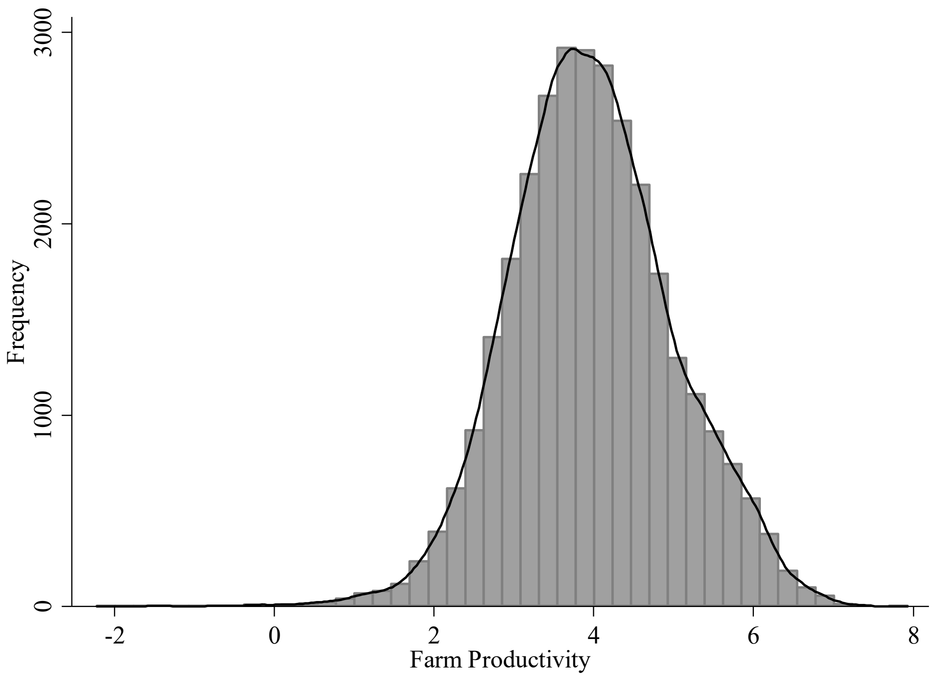
$$\frac{Y^e}{Y^a} = \frac{\sum_i y^e}{\sum_i y^a} ,$$

where $Y^e$ is aggregate efficient output, $y^e = s_i \left(k_i^e\right)^{\theta_k} \left(l_i^e\right)^{\theta_l}$ is farm-level efficient output, $Y^a$ is aggregate actual output, and $y^a = s_i k_i^{\theta_k} l_i^{\theta_l}$ is actual output. The calculation of actual output abstracts from rain and land quality was done in order to make it them comparable to the efficient output. Of note here is the fact that the output gain was also a TFP gain because the total amounts of capital and land and the number of farmers were fixed quantities.

## 3. RESULTS

Figure 1 plots the distribution of the natural logarithm of farm-level TFP $\ln(s_i)$, showing clearly a large productivity dispersion and a long left tail. This result indicates that the productivity of some farmers fell considerably below the average.

**Figure 1.** Distribution of Farm Productivity $s_i$




Note: Farm-level productivity or TFP has been naturally logged.

Table 1 reports various measures of dispersion of the natural logarithm of farm-level TFP $\ln(s_i)$, including the standard deviation, the interquartile range, and the interdecile range. The dispersion of farm productivity was less than that of manufacturing plant productivity in Thailand but was comparable to levels in Malawi and the United States.

**Table 1.** Dispersion of Farm Productivity and Manufacturing Plant Productivity

| | Farms | | | Manufacturing Plants |
|---|---|---|---|---|
| | Thailand (2013) | Malawi (2010/11) | USA (1990) | Thailand (2006) |
| Standard deviation | 1.03 | 1.19 | 0.80 | 1.59 |
| $75^{th}$ – $25^{th}$ percentile | 1.33 | 1.15 | 1.97 | 2.18 |
| $90^{th}$ – $10^{th}$ percentile | 2.63 | 2.38 | 2.50 | 4.12 |
| Observations | 31,239 | 7,157 | - | 49,547 |

Note: Statistics are for the natural logarithm of productivity ln($s_i$). The second, third, and fourth columns report statistics obtained from Restuccia and Santaeulalia-Llopis (2017), Adamopoulos and Restuccia (2014), and Dheera-aumpon (2014), respectively.

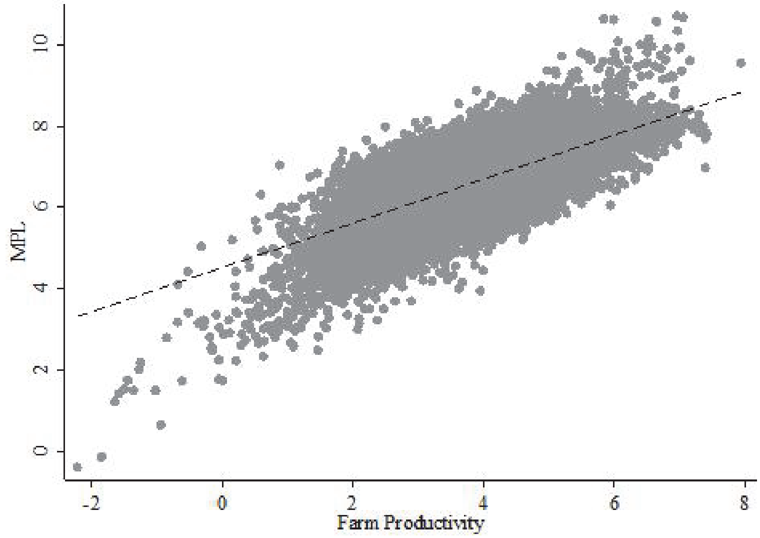
Table 2 reports the variance decomposition of farm-level output using the assumed production function. The key determinant of output variation across farms was farm-level productivity $s_i$, followed by the inputs of capital and land while rain and land quality, though these determinants played minor roles. Specifically, the variation in farm-level TFP explains approximately 73% of the total variation of output and the variation of inputs, including capital and quality-adjusted land, about 10%. When rain and land quality are assumed constant across farms, the variances and the contribution of farm-level TFP and inputs to the total output variation remain practically unchanged. So also in the case of Malawi investigated by Restuccia and Santaeulalia-Llopis (2017), rain and land quality played only small roles in output variation across farms.

**Table 2.** Variance Decomposition of Farm Output

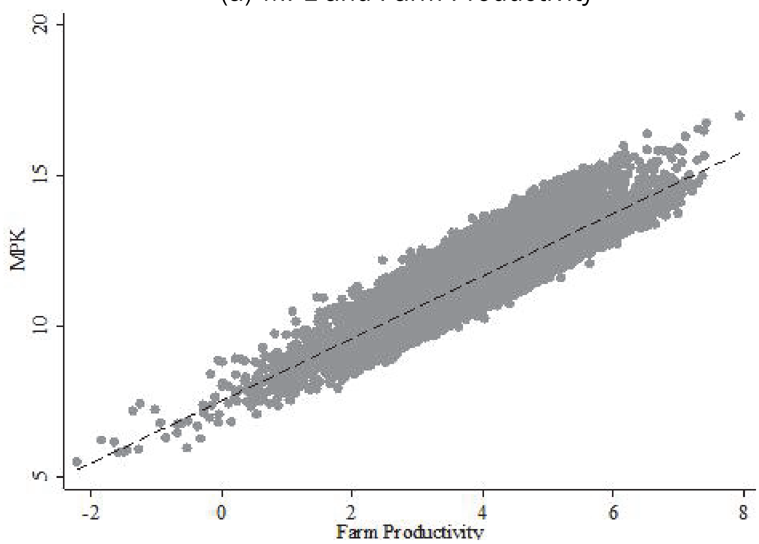
| | Benchmark | | $(\zeta_i = 1, q_i = 1)$ | |
|---|---|---|---|---|
| | Level | % | Level | % |
| $\mathrm{var}(y)$ | 1.462 | 100.0 | 1.462 | 100.0 |
| $\mathrm{var}(s)$ | 1.063 | 72.7 | 1.039 | 71.0 |
| $\mathrm{var}(\zeta)$ | 0.0069 | 0.5 | - | - |
| $\mathrm{var}(f(k, ql))$ | 0.147 | 10.1 | 0.147 | 10.0 |
| $2\,\mathrm{cov}(s, \zeta)$ | -0.028 | -1.9 | - | - |
| $2\,\mathrm{cov}(s, f(k, ql))$ | 0.288 | 19.7 | 0.139 | 9.5 |
| $2\,\mathrm{cov}(\zeta, f(k, ql))$ | -0.0152 | -1.0 | - | - |

Note: All variables have been naturally logged. The first two columns report results from the benchmark specification, in which rain and land quality were controlled for. The last two columns report the results abstracting from rain and land quality. In each case, the 'Level' column reports the variance and the '%' column the contribution to the total variance.

Figure 2. MPL, MPK and Farm Productivity




(a) MPL and Farm Productivity




(b) MPK and Farm Productivity

Note: Panel (a) reports marginal product of land (MPL) with respect to farm productivity. Panel (b) reports marginal product of capital (MPK) with respect to farm productivity. All variables have been naturally logged.

Figure 2 plots the natural logarithms of the marginal product of land (MPL) and the marginal product of capital (MPK) against the natural logarithm of farm-level TFP. Both MPL and MPK exhibit strong positive associations with farm-level TFP, with correlation coefficients of 0.71 and 0.88, respectively. This result is in contrast with efficient allocation, which is characterised by equalisation of both MPL and MPL across farms, and is thus indicative of extensive resource misallocation in rice farming in Thailand.

To illustrate the extent of resource misallocation more clearly, Figure 3 contrasts the actual allocation of land and capital with the efficient allocation of these resources, plotting both against farm-level TFP. All variables are presented in their natural logarithm form. When allocation is efficient, land size and capital strongly increase with farm productivity. In this case, the actual allocation of both land and capital contrasted strikingly with efficient allocation; thus the fitted lines of the actual allocations have flatter slopes and relatively looser mapping compared with those of efficient allocations. This finding confirms the magnitude of resource misallocation in Thai rice farming.

**Table 3.** Output Gain $Y^e/Y^a$

(a) Main Results

| | Full Sample | Bootstrap Simulations | | |
|---|---|---|---|---|
| | | Median | 5th percentile | 95th percentile |
| Output Gain | 1.67 | 1.67 | 1.64 | 1.70 |

(b) Within Productivity-$s_i$ Variation

| | Benchmark | Removing Within-$s_i$ Variation | | | |
|---|---|---|---|---|---|
| | | 5% | 10% | 20% | 100% |
| Output Gain | 1.67 | 1.63 | 1.61 | 1.58 | 1.43 |

(c) By Region

| | Bangkok | Central | North | Northeast | South | Mean |
|---|---|---|---|---|---|---|
| Output Gain | 1.22 | 1.41 | 1.53 | 1.66 | 1.68 | 1.50 |

Note: Entries are $Y^e/Y^a$ . In Panel (a), bootstraps median and confidence intervals were computed based on 500 simulations obtained from random draws with replacement. In Panel (b), within productivity-$s_i$ were removed by regressing land and capital on farm productivity and using the estimated relationships to construct measures of factor inputs from which residual variations have been partially or fully removed. Panel (c) reports the output gains that occurred within regions.

Table 3 reports the ratio of efficient aggregate output to actual aggregate output. The efficient aggregate output is equivalent to the aggregate output when marginal products are equalised across farms or in the absence of resource misallocation. Panel (a) reports the main results using the full sample: the output gain was 1.67-fold, or 67%, meaning that, were resource misallocation eliminated from Thai rice farming, output and productivity would increase by this factor. As alluded to above, a 67% gain would be considerable, though far less than the 148% gain in the Thai manufacturing sector reported by Dheera-aumpon (2014) or the 260% gain in the Malawian agricultural sector reported by Restuccia and Santaeulalia-Llopis (2017). The clear implication is that the extent to which resources were being misallocated in Thai rice production was significantly less than in either of these other sectors. Panel (a) also reports the results from 500 bootstrap simulations obtained from random draws with replacement. The 95% confidence interval of the output gain is (1.61, 1.70), indicating that this quantity was tightly estimated and confirming that extensive resource misallocation had a significant adverse effect on the aggregate output and productivity of Thai rice production.

As can be seen in Figure 3, resources were misallocated across farmers with various levels of productivity and were dispersed among those with similar levels of productivity. The former relationship is indicated by the fact that the fitted line of the actual allocation displays a flatter slope than that of efficient allocation and is vertically dispersed. Once more following Restuccia and Santaeulalia-Llopis (2017), I assessed the extent of the output gain associated with within-productivity misallocation by removing within-productivity $s_i$ variation from factor inputs and, in particular, regressing the natural logarithms of land size and capital separately on the natural logarithm of farm productivity. The estimated regression equations were then used to construct measures of factor inputs from which residual variations were partially or fully removed.

Panel (b) of Table 3 reports the results when 5, 10, 20, or 100% of within-productivity $s_i$ variation has been removed. As can be seen, the output gain decreased as this percentage increased. In the absence of within-productivity variation, resources can be seen to have been misallocated only across farmers with various levels of productivity. In this extreme case, the output gain was still 1.43-fold, or 43%, meaning that a large portion of the output gain can be explained in terms of resource misallocation across these farmers.

Since a reallocation of land across farmers nationwide seems impractical, I also report the output gain at the regional level, in Panel (c) of Table 3. The output gains were considerable in all regions except Bangkok, ranging from 1.41-fold for the central region to 1.68-fold for the southern. This result suggests that resource misallocation was most extensive in the southern region, followed by the north-eastern region.

In sum, the results indicate that resources were extensively misallocated in Thai rice farming over the period studied and that this misallocation had a significant negative effect on the aggregate productivity of this sector. The magnitude of the impact of misallocation was, however, less than that on Thai manufacturing sector.

## 4. ROBUSTNESS

Here I present robustness checks for the calculations of output gain. Specifically, I report the output gain at the group level classified in terms of education and membership in agricultural organisations in Table 4. The output gains are in all cases considerable. Thus, reallocation of resources among household-farms led by individuals with comparable levels of education resulted in gains ranging from 1.53- to 1.91-fold. Likewise, reallocation among farmers with similar levels of membership in agricultural organisations resulted in gains ranging from 1.64- to 1.73-fold.

**Table 4.** Output Gain $Y^e/Y^a$ – Robustness

(a) By Education Level

| | No Education | Lower than Elementary | Elementary | Secondary | Vocational | Higher Education | Others | Mean |
|---|---|---|---|---|---|---|---|---|
| Output Gain | 1.62 | 1.64 | 1.68 | 1.67 | 1.54 | 1.53 | 1.91 | 1.66 |

(b) By Membership of Agricultural Organisations

| | Non-Member | Member | Mean |
|---|---|---|---|
| Output Gain | 1.73 | 1.64 | 1.69 |

Note: Entries are $Y^e/Y^a$ . Panel (a) reports the output gains that occurred within groups classified by the educational level of the heads of households. Panel (b) reports the output gains that occurred within groups classified by membership of agricultural organisations.

Table 5 reports the output gains based on alternative measures of land size and output. Specifically, instead of the amount of land holdings for rice farming, I used the amount of land cultivated for rice farming to obtain an output gain of 1.55-fold. Also, rather than total rice output I used either in-season rice output or off-season rice output separately, with output gains of 1.51- and 1.47-fold, respectively. The fact that these output gains were in all cases considerable again confirmed the existence of extensive resource misallocation and its significant adverse impact on the aggregate productivity of the Thai rice farming sector.

**Table 5.** Output Gain $Y^e/Y^a$ – Alternative Measures

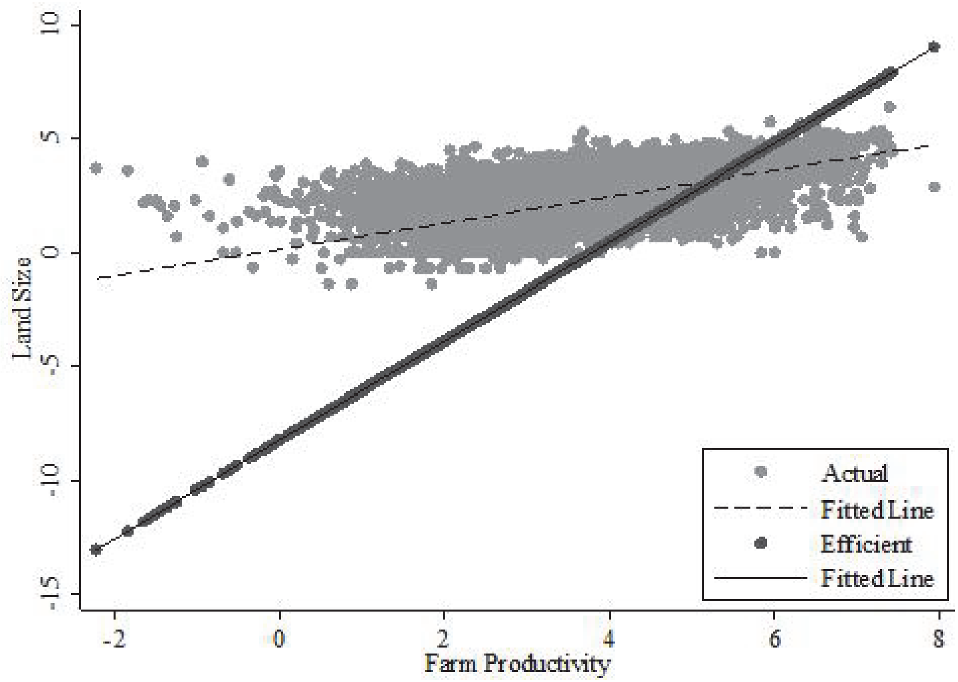
| | Benchmark | Cultivated Land Size | In-Season Rice | Off-Season Rice |
|---|---|---|---|---|
| Output Gain | 1.67 | 1.55 | 1.51 | 1.47 |

Note: Entries are $Y^e/Y^a$ . The first column reports the result from the benchmark specification using land holding for rice farming and total rice output. The second column reports the results using cultivated land size instead of land holding. The third and the forth columns report the results using in-season and off-season rice outputs instead of total rice output, respectively.

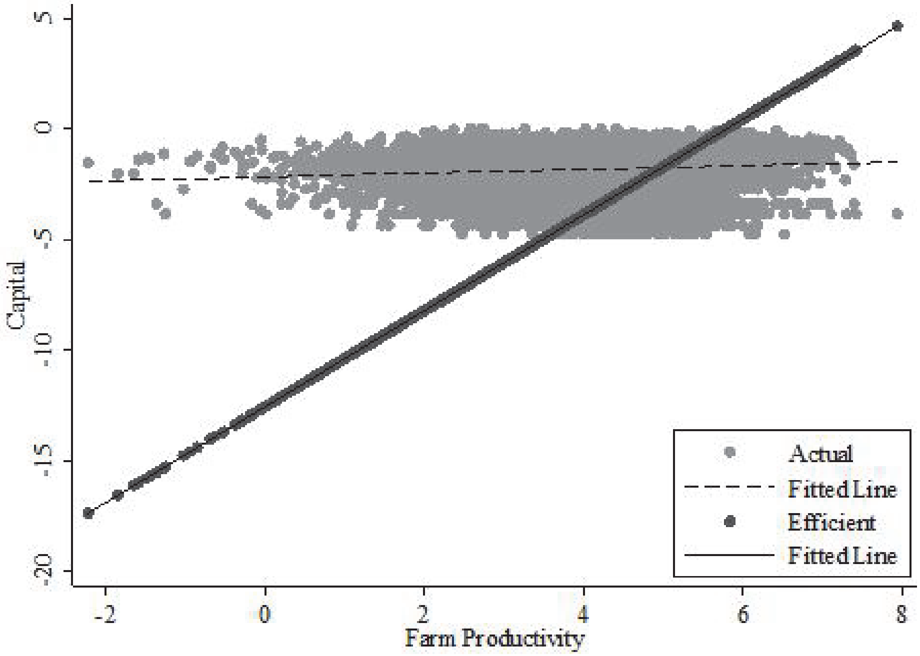
## 5. DISCUSSION

As Figure 3 shows, under a more efficient allocation of resources, high-productivity farmers would receive more land and capital than low-productivity farmers. Effective land reform policy, therefore, involves not merely reallocating land to reduce the landholdings of large landholders; and indeed such a policy would lead to a decrease in aggregate output and productivity. Thus an experiment reallocating land from farmers with holdings greater than 5 hectares to those with holdings below the median size indicated a resulting decrease in aggregate productivity of 2.7%. This result is consistent with that of a study by Adamopoulos and Restuccia (2014) on the imposition of a ceiling of 5 hectares on land holdings in the Philippines.

**Figure 3.** Land Size, Capital and Farm Productivity: Actual and Efficient Allocations




(a) Land Size and Farm Productivity




(b) Capital and Farm Productivity

Note: Panel (a) reports actual and efficient land size of farms with respect to farm productivity. Panel (b) reports actual and efficient capital of farms with respect to farm productivity. All variables have been naturally logged.

An effective allocation policy, then, would support high-productivity farmers with land and capital. Governments may not find it easy, however, to identify such farmers. The findings presented here do suggest one possible method. Specifically, regarding the relative productivity of farmers in relation to their membership in agricultural organisations, the differential between 4.06 for those who belonged and 3.81 for those who did not was found to be statistically significant at the 1% level. Governments could, therefore, target to support farmers who participate in such organisations.

## CONCLUSIONS

To study resource misallocation and its effect on the aggregate productivity of rice farming in Thailand, I applied the method used by Restuccia and Santaeulalia-Llopis (2017) to data for some 31,000 Thai household-farms obtained from the country's 2013 Agricultural Census. I found that a reallocation of resources, in particular land and capital, could increase the aggregate output and the productivity of Thai rice farming by approximately 1.67-fold, or 67%. While such a potential gain is not small, it is less than those predicted in other studies for either the Thai manufacturing sector or the Malawian agricultural sector. The implication is that resources have been misallocated in Thai rice production, but that the problem is not as severe as it can be in other contexts.

Contrasting actual with efficient allocation, I found the distribution of land and capital for rice farming in Thailand to be sub-optimal, with high-productivity farmers receiving too little and low-productivity farmers receiving too much of these resources. A policy designed to allocate resources more efficiently would favour the former. A further finding presented here is that farmers who belonged to agricultural organisations tended to be more productive than those who did not, the implication being that members of such organisations could be targeted for preferential allocation of land and equipment in governmental policies in the furtherance of efficient resource allocation.

I conclude by stressing that an effective policy in this regard cannot involve simply reducing the landholdings of large landholders, for doing so would lower the aggregate output and thus decrease aggregate productivity.

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