Misallocation or Measurement Error: Evidence on Vietnam's Agriculture

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Abstract: We examine misallocation by investigating how measurement errors in output and inputs affect the estimation of agricultural productivity loss associated with resource misallocation. We find that measurement errors account for a substantial part of the estimated total factor productivity (TFP) variations (30-45% at the national level). Correspondingly, failing to account for measurement errors would considerably overestimate the gains from resource reallocation. Based on the preferred Two-Stage least squares (2SLS) estimation of the production function, measurement errors in both output and inputs will lead to an overstatement of production gains by 2-3-fold if not adjusted in productivity estimation. The results are consistent regardless of whether the analysis is explored by analyzing household productivity variation across years or across households within local communes. The findings caution against relying on estimates unadjusted for measurement error of potential gains from reallocation in cost-benefit analysis of reallocation. Certain caveats and assumptions of the analysis are discussed in the paper.

Key Words: Misallocation, Productivity, Measurement error, Methodology

1. Introduction

Optimization of resource allocation maximizes the total production of an economy endowed with finite productive resources and efficient productive individuals heterogeneous in total factor productivities (TFP) (Restuccia and Rogerson 2008; Hsieh and Klenow 2009). Misallocation represents a departure from this optimal allocation, resulting in income loss and increased dispersion in output per worker. In practice, large variations in productivity have been observed across sectors and between establishments in narrowly defined industries within a sector; moreover, the variation tends to be greater in poor countries than in rich countries (Restuccia and Rogerson 2008, 2013; Hsieh and Klenow 2009; McMillan, Rodrik, and Verduzco-Gallo 2014; Porzio 2016; Bento and Restuccia 2017).

Motivated by these observations, a substantial and growing body of literature on resource misallocation has emerged (Restuccia and Rogerson 2008; 2013; Hsieh and Klenow 2009; Banerjee and Moll 2010; Bartelsman, Haltiwanger, and Scarpetta 2013; Hopenhayn 2014; and Bento and Restuccia 2017). The emerging evidence from these empirical studies suggests that misallocation has played a significant role in explaining the low level of aggregate productivity in low-income countries and the world's income gap.

The agricultural sector holds special significance and importance in the developing world (Gollin, Parente, and Rogerson 2002). According to estimates from the International Labor Organization (ILO), approximately 58.8% of the labor force was engaged in the agriculture sector in low-income countries in 2022, with figures of 56% for Eastern and Southern Africa and 45% for Western and Central Africa. Misallocation within this sector is often attributed to market constraints and local restrictions that hinder the efficient distribution of productive resources (Banerjee and Moll 2010;

Restuccia and Rogerson 2017), and constraints and imperfections are notoriously prevalent in the agricultural land and labor markets in developing countries.

Given the significance of the agricultural sector in these economies, a considerable portion of the literature has focused on misallocation within agriculture (see for example, Gollin, Lagakos, and Waugh 2014; Adamopoulos and Restuccia 2014; Restuccia 2016 for the assessments of the potential income gap resulting from such misallocation). Previous studies reveal significant output gains through reallocation, with estimates ranging from 57% in China and 80% in Vietnam to 140% in Ethiopia and 260% in Malawi (Ayerst, Brandt, and Restuccia 2020; Adamopoulos et al. 2022; Chen, Restuccia, and Santaeulàlia-Llopis 2022, 2023).

An empirical challenge in assessing misallocation lies with the measurement of factor elasticities and TFP, which hinge on accurate measures of inputs and production outputs. If the input and outputs are measured with errors, the estimated productivity gain resulting from resource reallocation could be biased (Gollin and Udry 2021). In reality, measurement errors are a ubiquitous part of data analysis and pose a significant estimation challenge.

In agriculture, inaccurate estimates or imperfect reporting are significant sources of measurement errors in both inputs and outputs (Abay, Bevis, and Barrett 2021). One traditional method to reduce errors in production input data is to require respondents to maintain continuous production diaries (Deininger et al. 2012). To reduce the widespread measurement errors of land size, researchers rely on methods such as the compass-and-rope approach (Dillion et al. 2019) or, more recently, the use of Global Positioning System (GPS) data (Carletto et al. 2013; 2015; Kilic 2017). The crop-cut method is one approach to address the measurement error of output data (Abay et al. 2019; Desiere and Jolliffe 2018; Gourley et al. 2019).

There is a growing body of recent literature that explores the impact of measurement error on estimates of the relationship between farm size and productivity (Desiere and Jolliffe 2018; Abay et al. 2019; Ayalew et al. 2024). Abay (2020) investigates the relationship between measurement error and marginal returns to modern agricultural inputs. Findings from these studies suggest a correlation between output and input use and their respective measurement errors, highlighting the possibility of non-classical measurement error. Cohen (2019) argues that even GPS measurements may still be subject to classical measurement errors, primarily due to ‘position error’ in satellites and human errors in GPS device operation (Bogaert, Delincé, and Kay 2005; Bogaert, Delincé, and Kay 2005; Keita and Carfagna 2009).

Despite the widespread recognition of measurement errors in agriculture and the increasing literature dedicated to addressing this issue in studies examining the relationship between farm size and productivity, the issue of measurement error has largely been overlooked in the emerging literature on resource misallocation (e.g., Ayerst, Brandt, and Restuccia 2020; Adamopoulos et al. 2022; Chen, Restuccia, and Santaeulàlia-Llopis 2022, 2023). There are a few exceptions, such as Bils, Klenow, and Ruane (2021), Aragon, Restuccia, and Rud (2021), and Gollin and Udry (2021).

Bils, Klenow, and Ruane (2021) use data from manufacturing sectors in both India and the U.S. to identify the measurement error stemming from the rates of revenue and input growth in response to productivity shocks. They find that measurement error contributes to a greater dispersion in revenues per input in the U.S. and the potential gains from reallocation undergo a more significant reduction in the adjustment process compared to India.

Using agricultural data from Tanzania and Uganda, Gollin and Udry (2021) find that the misallocation diminishes significantly after accounting for measurement errors in their study.

Apart from the aforementioned measurement and reporting errors, Gollin and Udry (2021) identify two other sources of measurement errors in agricultural production data. One is linked to the stochastic nature of agricultural production, which is associated with the vagaries related to weather, pests, and crop diseases. The other is related to shocks occurring late in the production season after farmers have already made their production decisions (Gollin and Udry 2021). These late-season shocks could include adverse weather events, pests, or disease shocks that occur sufficiently late in the growing season that farmers are unable to effectively respond to them. They find that potential output in an efficiently allocated scenario is overestimated by a factor of 2.6 in Tanzania and an even higher factor of 3.7 in Uganda. Similar to the findings of Bils, Klenow, and Ruane (2021), they find that this overestimation is more pronounced in less wealthy countries where measurement errors exhibit greater variability.

The method of Gollin and Udry (2021) heavily relies on a structure of plot data. They use data from multiple plots growing the same crop managed by the same individual or household within a season of a year, creating a panel. This panel structure ensures that market distortions are held constant so that the distortion-induced variance is eliminated. Then by employing a normalization that involves TFP and factor-specific productivity, they infer the variances in measurement errors in outputs and inputs to correct misallocation accordingly. They then proceed to infer productivity and measurement error-induced variances.

In contrast, Aragon, Restuccia, and Rud (2021) presents several arguments against the use of plot-level data in misallocation calculation[1]. They provide empirical evidence suggesting that plot-level

[1] According to Aragon, Restuccia, and Rud (2021), the main reasons why using plot-level data is likely to exaggerate the measurement error include (1) a much higher level of productivity dispersion to begin with, and (2) the practical issue to separate inputs by plots.

data tend to overestimate the impact of measurement errors, leading to estimates that do not agree with the literature at large.

In this paper, we follow Aragon, Restuccia, and Rud (2021) and utilize panel data at the household level from Vietnam to identify within-household variance in measurement errors. As robustness checks, we also estimate the within-commune variance in measurement errors. Additionally, we differentiate the estimates for all crops versus rice crops, as well as for the Southern region versus the Northern region. My method relies on three key assumptions.

The first assumption is that the measurement errors are classical measurement errors, orthogonal to their true value and with each other. This assumption is crucial for effectively separating and identifying the variance of measurement error.[2] The second assumption posits that productive households operate efficiently within the constraints they face. The final assumption relates to intermediate inputs and facilitates the identification of a subset of measurement error variances. It assumes minimal change within a household over time and little variance in the shadow prices and elasticities for intermediate inputs within a commune. By holding intermediate input use constant, we can identify variances of measurement errors in intermediate inputs and output. The assumptions can be empirically tested against conditions derived from the household model.

Finally, using crop data from Vietnamese farming households, we aim to infer the actual output gap after adjusting for measurement error. We find that nationwide, up to 45% of the variation in the standard TFP estimate comes from measurement error and allocation-unrelated elements. Using the production residual as an estimate for TFP, the raw estimate of potential gains from

[2] One limitation of this study is that it cannot deal with non-classical measurement errors. Previous studies such as Gollin and Urdy (2021) and Aragon, Restuccia, and Rud (2021) make the same assumption on measurement errors in their studies.

reallocating is 139% of the observed revenue for all crops. Heterogeneity analysis between the Northern and Southern regions and between all crops and rice investigates regional comparative advantages in different crops.

The paper makes three contributions. First, it contributes to the scant literature that directly addresses measurement error in misallocation analysis, and it is the first such study using data from Vietnam[3]. Second, as opposed to the usual requirement for high-quality data to address measurement error, this method is cost-saving on data by achieving misallocation adjustment for measurement error using household-level survey data. While plot- and parcel-level data tend to overestimate the impact of measurement error, household-aggregate data reduce both the magnitude and the dispersion of measurement error (Aragon, Restuccia, and Rud 2021). The household-level analysis also allows for convenient interpretation and easy placement within the tradition of the literature on misallocation. Regarding methodology, a key assumption in the paper involving intermediate inputs is observationally inspired, testable, and not too restrictive. Third, by exploring the difference between south and north, and between all crops and rice crops only, the findings of this study are of policy relevance. Given the historical difference in property rights between the North and South regions, whether and to what extent resource misallocation differs between the two regions is of academic and policy significance.

The remainder of the paper is as follows. Section 2 outlines the theoretical model. Section 3 describes the data set. Section 4 presents the estimation strategy. Section 5 presents the results, and section 6 concludes the paper.

[3] Ayerst, Brandt, and Restuccia (2020) investigates agricultural misallocation in Vietnam without adjusting for measurement error.

2. Theoretical Model

2.1. Production function and measured total factor productivity:

The model will assume a Cobb-Douglas production function of the form:

$$Y_{ht}^{o} = e^{\epsilon_{Yht}} e^{\omega_{Yht}} \boldsymbol{e^{\beta W_{ht}}} (L_{ht})^{\alpha_{Lht}} (N_{ht})^{\alpha_{Nht}} (M_{ht})^{\alpha_{Mht}}$$

where Y_{ht}^{o} is the observed output of household h at time t, $J \in \{L, N, M\}$ are land, labor, and intermediate inputs (seeds, saplings, fertilizers, pesticides/herbicides, energy, irrigation, maintenance, and other), respectively, used in the household's crop production. Output elasticities of factor inputs α_{Jht} are allowed to vary across households and time to capture the differences in land and other input's quality and intensity. $\boldsymbol{W_{ht}}$ are observable household, land characteristics, and late-seasoned shocks. The parameter ω_{Yht} denotes the total factor productivity (TFP) and is unobservable to the researcher but known to the household. Finally, the classical error term ϵ_{Yht} is unobservable to the researcher as well as unknown to farmers. Rewrite

$$Y_{ht}^{o} = Y_{ht} e^{\epsilon_{Yht}}$$

where Y_{ht} denotes the household's true output. Measurement errors in inputs J are similarly modeled:

$$J_{ht}^{o} = J_{ht} e^{\epsilon_{Jht}}$$

where J_{ht}^{o} is the reported input, J_{ht} is the true value of input J of household h in time t and ϵ_{Jht} is the corresponding measurement error in factor input J.

All the components of the vector $(\epsilon_{Yht}, \epsilon_{Jht})$ are subject to classical measurement error assumptions and orthogonal with each other. The production is re-expressed with lowercase to represent their logarithms.

$$
\begin{aligned}
y_{ht}^{o} &= \epsilon_{Yht} + \omega_{Yht} + \boldsymbol{\beta W_{ht}} + \sum_{J} \alpha_{Jht} j_{ht} \\
&= \epsilon_{Yht} + \omega_{Yht} + \boldsymbol{\beta W_{ht}} + \sum_{J} \alpha_{Jht} j_{ht}^{o} - \sum_{J} \alpha_{Jht} \epsilon_{Jht}
\end{aligned}
\tag{1}
$$

An estimation of the production function estimates the coefficients β and α_J the expected values of α_{Jht}. The production residuals provide estimates for the household TFPs that are calculated as:

$$
\begin{aligned}
\ln \widehat{TFP}_{ht} &= y_{ht}^{o} - \boldsymbol{\widehat{\beta} W_{ht}} - \sum_{J} \widehat{\alpha_J} j_{ht}^{o} \\
&= \epsilon_{Yht} + \omega_{Yht} + \boldsymbol{\beta W_{ht}} + \sum_{J} \alpha_{Jht} j_{ht}^{o} - \sum_{J} \alpha_{Jht} \epsilon_{Jht} - \boldsymbol{\widehat{\beta} W_{ht}} - \sum_{J} \widehat{\alpha_J} j_{ht}^{o} \\
&= \epsilon_{Yht} + \sum_{J} \widehat{\alpha_J} \epsilon_{Jht} + \omega_{Yht} + (\boldsymbol{\beta} - \boldsymbol{\widehat{\beta}}) \boldsymbol{W_{ht}} + \sum_{J} (\alpha_{Jht} - \widehat{\alpha_J}) j_{ht}^{o} - \sum_{J} (\alpha_{Jht} - \widehat{\alpha_J}) \epsilon_{Jht} \\
&= \epsilon_{Yht} + \sum_{J} \widehat{\alpha_J} \epsilon_{Jht} + \omega_{Yht} + (\boldsymbol{\beta} - \boldsymbol{\widehat{\beta}}) \boldsymbol{W_{ht}} + \sum_{J} (\alpha_{Jht} - \widehat{\alpha_J}) j_{ht}
\end{aligned}
$$

In the limit, with consistent estimators of the production elasticities, the production residuals approach:

$$
\ln \widehat{TFP}_{ht} \to \left(\epsilon_{Yht} + \sum_{J} \alpha_J \epsilon_{Jht} \right) + \omega_{Yht} + \sum_{J} (\alpha_{Jht} - \alpha_J) j_{ht}
$$

The second and third terms in the limit ω_{Yht}, and $\sum(\alpha_{Jht} - \widehat{\alpha_J})j_{ht}$ reflect the true factor-neutral and factor-specific productivities, and are both assumed known to farmers. Together, they are informative about household productivities and form the true TFP, that is $\ln TFP_{ht} = \omega_{Yht} + \sum_J(\alpha_{Jht} - \alpha_J)j_{ht}$. The first term $\epsilon_{ht} \equiv \epsilon_{Yht} + \sum_J \alpha_J \epsilon_{Jht}$ with $E(\epsilon_{ht}) = 0$ and $Var(\epsilon_{ht}) = Var(\epsilon_{Yht}) + \sum_J \alpha_J^2 Var(\epsilon_{Jht})$ is the aggregate measurement error in output and inputs. As far as allocative efficiency is concerned, ϵ_{ht} provides no information on efficiency gain through reallocation of factor resources and only serves as noise.

One is often interested in the distribution of measured TFP because it is a tool to characterize efficient factor allocation. With the classical measurement error and orthogonal assumptions, the variance of measured TFP can be decomposed into two parts:

$$Var\left(\ln \widehat{TFP}_{ht}\right) = Var\ (\epsilon_{ht}) + Var\ \left(\omega_{Yht} + (\boldsymbol{\beta} - \widehat{\boldsymbol{\beta}})\boldsymbol{W_{ht}} + \sum(\alpha_{Jht} - \widehat{\alpha_J})j_{ht}\right) \quad (2)$$

The first term shows that measurement error ϵ_{ht} becomes an additional source of variation in the production residual that does not represent actual variation in productivity. For allocative efficiency purposes, it is irrelevant. To see how this added variance presents a problem, section 2.2 characterizes the efficiency allocation and outcome, followed by the implications of measurement error on perceived distortion and estimates of potential income gain through factor reallocation in section 2.3. Then section 2.4 details how the measurement error components ϵ_{Yht} and ϵ_{Jht} of ϵ_{ht} can be measured and removed from the TFP variance estimate in (2).

2.2. Characterization of efficient output and allocation of factors

In this section, to systematically characterize the optimal allocation, we will assume away heterogeneity in output elasticities. Furthermore, in this exercise, the time subscript t is implied and dropped for convenience purposes. Consider a Cobb Douglas production technology in year t of the form $Y_h = \exp \omega_h \, L_h^{\alpha_L} N_h^{\alpha_N} M_h^{\alpha_M}$. In the efficient allocation, the optimal inputs and output solve the following problem:

$$\underset{L_h, X_h}{\text{Max}} \sum_h \exp \omega_{Yh} \prod\nolimits_J J^{\alpha_J} \text{ s.t } \sum_h J_h = \bar{J}$$

The first order condition implies that efficient allocation requires equalized marginal product of each factor across households, i.e.

$$\frac{Y_h^*}{J_h^*} = \frac{Y_g^*}{J_g^*} = \frac{\bar{Y}}{\bar{J}}$$

Let $s_h \equiv \frac{J_h^*}{\bar{J}}$ define the optimal share of resources for each household from the total pool of resources. It follows that $s_h = \frac{Y_h^*}{\bar{Y}} = \frac{\exp \omega_{Yh} \prod_J (s_h \bar{J})^{\alpha_J}}{\bar{Y}}$ and therefore is constant across factor inputs J. The social planner's solution for s_h is $s_h = \left(\frac{\prod_J \bar{J}^{\alpha_J}}{\bar{Y}}\right)^{\frac{1}{1-\sum_J \alpha_J}} \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)$.

Since household shares add up to 1, i.e.

$$\sum\nolimits_h s_h = 1 \Rightarrow \left(\frac{\prod_J \bar{J}^{\alpha_J}}{\bar{Y}}\right)^{\frac{1}{1-\sum_J \alpha_J}} \sum\nolimits_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right) = 1 \Rightarrow \left(\frac{\prod_J \bar{J}^{\alpha_J}}{\bar{Y}}\right)^{\frac{1}{1-\sum_J \alpha_J}} = \frac{1}{\sum_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)},$$

this share can be alternatively expressed as $s_h = \frac{\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}{\sum_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}$. The idea of this expression is simple and intuitive: a household's optimal share of input factor is strictly increasing in its TFP, and is proportionate to its productivity relative to other households.

2.3. Implications of measurement error

In the absence of measurement error, the first-order condition provides several ways to measure how far the existing allocation is from optimality. Productivities, $\frac{Y_h}{J_h}$, are proportional to the marginal product of factors, and are constant across households in efficient allocation. Similarly, the cross-factor ratios, $\frac{J_{ht}}{I_{ht}}$, are indicative of allocative efficiency. The general idea is that, in optimal allocation, productivities and cross-factor ratios are equalized across households, and that a higher dispersion indicates a higher level of distortion, and thus factor misallocation.

In the presence of measurement error, however, these observations would be misguided, since measurement error increases the dispersion of observed factor productivities and observed cross-factor ratios alike. For illustration, let us look at the variance of the logarithm of the measured crop yields:

$$Var\left(\ln\left(\frac{Y_h^o}{L_h^0}\right)\right) = Var(y_h^o - l_h^o) = Var(\epsilon_{Yh} - \epsilon_{Lh}) + Var(y_h - l_h)$$

$$> Var(y_h - l_h) = Var\left(\ln\left(\frac{Y_h}{L_h}\right)\right)$$

Similarly, it can easily be proved that the presence of measurement error also generates more dispersion in other observed factor productivities as well as any factor ratio combination. Observing these measures and letting them inform us of the existing level of distortion, therefore, can exaggerate the misallocation problem. If measurement error varies greatly, it can create a lot of noise in the distribution of these distortion measures that otherwise may have low spreads.

Next, we will quantify the overstatement in potential gains from reallocation. If resources are to be optimally distributed, the observed output is:

$$Y_h^{o*} = \exp(\epsilon_h)\exp(\omega_{Yh})\left(\frac{\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}{\sum_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}\right)^{\sum_J \alpha_J} \prod_J \bar{J}^{\alpha_J}$$

$$= \exp(\epsilon_h)\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\left(\sum_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\right)^{-\sum_J \alpha_J} \prod_J \bar{J}^{\alpha_J}$$

$$= \exp(\epsilon_h)\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\left(NE\left(\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\right)\right)^{-\sum_J \alpha_J} \prod_J \bar{J}^{\alpha_J}$$

In expectation, optimal observed output turns out to be:

$$E(Y_h^{o*}) = E(\exp(\epsilon_h))\left(E\left(\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J} N^{-\sum_J \alpha_J} \prod_J \bar{J}^{\alpha_J}.$$

In practice, researchers use the production function residuals to generate TFP estimates and to generate estimates of optimal factor allocation and output. As shown previously in section 2.1, these TFP estimates contain measurement errors and are in fact "inconsistent" with the true TFP. The estimated optimal output in an allocation planned according to the confounded TFP estimates is

$$\widehat{Y_h^{o*}} = \exp(\omega_{Yh} + \epsilon_h)\left(\frac{\exp\left(\frac{\omega_{Yh}+\epsilon_h}{1-\sum_J \widehat{\alpha_J}}\right)}{\sum_h \exp\left(\frac{\omega_{Yh}+\epsilon_h}{1-\sum_J \widehat{\alpha_J}}\right)}\right)^{\sum_J \widehat{\alpha_J}} \prod_J \bar{J}^{\widehat{\alpha_J}}$$

A similar derivation as above will reveal the expected value of estimated output as:

$$E\left(\widehat{Y_h^{o*}}\right) = \left(E\left(\exp\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J} \left(E\left(\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J} N^{-\sum_J \alpha_J} \prod_J \bar{J}^{\alpha_J}$$

To compare the estimated and true optimal outputs, simply take their ratio:

$$\frac{E\left(\widehat{Y_h^{o*}}\right)}{E\left(Y_h^{o*}\right)} = \frac{\left(E\left(\exp\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J}}{E(\exp(\epsilon_h))}$$

Within the caveat of a decreasing returns to scale Cobb-Douglas production function, $1-\sum_J \alpha_J > 0$. Apply Jensen's Inequality, it can be seen that

$$\left(E\left(\exp\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J} > \left(\exp\left(E\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J}$$

$$= \exp\left(\left(1-\sum_J \alpha_J\right) E\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right) = E(\exp(\epsilon_h)),$$

and therefore $E\left(\widehat{Y_h^{o*}}\right) > E\left(Y_h^{o*}\right)$, i.e optimal outputs are overestimated using the estimated TFP confounded by measurement error. To quantify the magnitude of optimal output overestimation, assume ϵ_h to follow a normal distribution. Then,

$E(\exp(\epsilon_h)) = \exp\left(E(\epsilon_h) + \frac{Var(\epsilon_h)}{2}\right) = \exp\left(\frac{Var(\epsilon_h)}{2}\right)$, and

$$\left(E\left(\exp\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)\right)\right)^{1-\sum_J \alpha_J} = \left(\exp\left(E\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right) + \frac{Var\left(\frac{\epsilon_h}{1-\sum_J \alpha_J}\right)}{2}\right)\right)^{1-\sum_J \alpha_J}$$

$$= \left(\exp\left(\frac{Var(\epsilon_h)}{2\left(1-\sum_J \alpha_J\right)^2}\right)\right)^{1-\sum_J \alpha_J} = \exp\left(\frac{Var(\epsilon_h)}{2\left(1-\sum_J \alpha_J\right)}\right)$$

$$\Rightarrow \frac{E\left(\widehat{Y_h^{o*}}\right)}{E(Y_h^{o*})} = \exp\left(\frac{Var(\epsilon_h)}{2\left(1-\sum_J \alpha_J\right)} - \frac{Var(\epsilon_h)}{2}\right) = \exp\left(\frac{Var(\epsilon_h)\sum_J \alpha_J}{2\left(1-\sum_J \alpha_J\right)}\right) \tag{3}$$

It can be concluded that under our set of assumptions, using production residuals as TFP estimates to inform about the efficient allocation overstates the misallocation gap, the magnitude of which depends on the returns to scale $\sum_J \alpha_J$ of the production technology, as well as variance $Var(\epsilon_h)$ of the aggregate measurement error. Elasticities α_J can be consistently estimated in the production function. The remaining task is to calculate the variance of measurement error $Var(\epsilon_h)$, separating it from the actual productivity variance. In order to do so, next we turn to the household's problem.

2.4. Separation of productivities and measurement errors

Assume that households are efficient and maximize profit subject to their shadow input prices $p_{Jh} = (p_{Lh}, p_{Nh}, p_{Mh})$ relative to normalized output price $p_Y = 1$.

$$\text{Max}\, p_Y Y_h - \sum_J p_{Jh} J_h$$

The first order condition of the problem $J_h = \frac{\alpha_{Jh} Y_h}{p_{Jh}}$ implies:

$$Y_h = \left(e^{\beta W_h} e^{\omega_{Yh}}\right)^{\frac{1}{1-\sum_J \alpha_{Jh}}} \prod\nolimits_J \left(\frac{\alpha_{Jh}}{p_{Jh}}\right)^{\frac{\alpha_{Jh}}{1-\sum_J \alpha_{Jh}}}$$

The output and input solutions in log are:

$y_h = \frac{1}{1-\sum_J \alpha_{Jh}}\left(\beta W_{ht} + \omega_{Yh} + \sum_J \alpha_{Jh}\left(\ln \alpha_{Jh} - \ln p_{Jh}\right)\right)$ and $j_h = y_h + \left(\ln \alpha_{Jh} - \ln p_{Jh}\right)$

It is not possible in this paper to empirically separate factor-specific productivities α_{Jh} from distortions in the corresponding market p_{jh}. Therefore, we combine them through the term $\omega_{Jh} \equiv \ln \alpha_{Jh} - \ln p_{Jh}$, then j_h is rewritten as $j_h \ = y_h + \omega_{Jh}$,

Where ω_{Jh} represents both a household's ability to use factor J and the idiosyncratic distortion they face in that factor market. We call ω_{Jh} factor J-specific productivity-distortion. A household's profit maximizing solution for the logarithm of factor demand J is the sum of its total output y_h and factor J- specific productivity-distortion ω_{Jh}.

The observed factor demands and observed production outcome are simply the sum of their true value and their measurement errors.

$$y_h^o = \epsilon_{Yh} + y_h \tag{4}$$

$$j_h^o = \epsilon_{Jh} + y_h + \omega_{Jh}$$

This set of rules breaks down the observable factor demands and production output in the left-hand side of (4) into components that are known $(\omega_{Yh}, \omega_{Jh})$ and unknown $(\epsilon_{Yh}, \epsilon_{Jh})$ to farmers at the time of decision making. For the sake of convenience, some short-hand notations are defined as follows: variances of output and input measurement errors $\left(Var(\epsilon_{Yh}), Var\left(\epsilon_{Jh}\right)\right) = (\sigma_{\epsilon Y}^2, \sigma_{\epsilon J}^2)$, variances of output productivity and input-specific productivities-distortions $\left(Var(y_h), Var\left(\omega_{Jh}\right)\right) = (\sigma_Y^2, \sigma_J^2)$, and covariances between any two productivities ($\left(Cov\left(y_h, \omega_{Jh}\right), Cov\left(\omega_{Ih}, \omega_{Jh}\right)\right) = \left(\sigma_{YJ}, \sigma_{IJ}\right)$.

Since measurement errors are assumed to be independent of each other and of productivities, expressing (4) in terms of variances and covariances provides the following set of equations:

$$Var(y_h^o) = \sigma_{\epsilon Y}^2 + \sigma_Y^2$$

$$Var(j_h^o) = \sigma_{\epsilon J}^2 + \sigma_Y^2 + \sigma_J^2 + 2\sigma_{YJ} \qquad (5)$$

$$Cov(y_h^o, j_h^o) = \sigma_Y^2 + \sigma_{YJ}$$

$$Cov(i_h^o, j_h^o) = \sigma_Y^2 + \sigma_{YI} + \sigma_{YJ} + \sigma_{IJ}$$

This system is short of identifying all variances of measurement error, with the number of unknowns exceeding the number of equations by $J + 1$. Certain assumptions are needed to identify the key parameters of the system, which will be further discussed in a later section.

In the next section, we will present the data used in this study, and explore the potential of market distortions and factor misallocation, before moving on to outline the identification strategies we will apply on this dataset in section 4.

3. Data

This paper is based on three rounds 2012, 2014, and 2016 of household data from the Vietnam Access to Resources Household Survey (VARHS). The survey is collected by the United Nations University World Institute for Development Economics Research (UNU WIDER) and provides a household panel representative of the rural population in 12 provinces across all regions of the country in 2006. The subsequent waves of data follow up on previously selected households with additional households surveyed in 2008 and 2012.

While we draw on households' all crop farming activities, special focus is also given to the rice crops and those households that exclusively grow rice. A comparison between the aggregate and rice crops provides insights into the magnitude of measurement error impact on lower-level data and aggregate data usage. If what Aragon, Restuccia, and Rud (2021) assert is true, a higher dispersion of measurement error is expected in the rice crop function relative to the household-level aggregate crops.

Physical outputs and revenue are given for each specific crop production for different annual crops, perennial crops, fruits, and forestry, which is aggregated to the household total[4]. Despite that data on factor inputs are scarcer in detail for each specific crop in the survey, household level and rice crop information are reported.

Data on factor demand used in this paper includes land use area, labor, and intermediate inputs (i.e. expenses on seeds, saplings, fertilizers, pesticides/herbicides, energy, irrigation, maintenance, and other costs). For production function identification, we control for self-reported land characteristics (distance from the household, land value, irrigation, land use rights certification, crop restriction) and quality (below, average, or above local average) aggregated from plot level, as well as household demographics including household head's age, gender, and educational level. Further controls are weather shocks (drought). Some other household shocks are employed are excluded variables (avian flu, change in commodity price, whether household's head is sick).

[4] The annual crops reported are rice, maize, potato, sweet potato, cassava, peanuts, soybean, vegetables, and other annual crops. The perennial crops include coffee, tea, cocoa, cashew nuts, sugar cane, pepper, rubber, medicinal trees, and other perennial crops. With the exception of aggregate categories like vegetables, other annual crops, fruits, and forestry products, where physical production is not available, physical production and revenue were reported for all of the listed crops.

The sample is summarized in Table 1. The main analysis is drawn from 8264 household observations in three separate years, 2,887 in 2012, 2861 in 2014, and 2,516 in 2016, which account for 3140 unique crop-growing households in the sample. Geographically, these households belong to 492 administrative communes in 138 districts drawn from 12 provinces from across the regions of Vietnam, which can be divided into North and South regions. On average, households in the sample grow more than two different crops a year. To examine misallocation and measurement error in the rice crop production, we also focus on the subsample of single rice-crop households[5]. This sample narrows the number of observations down to 2,755 across all three years.

Table 2, which includes two panels, panel A for any household that grow crops, and panel B for rice specialized households, gives insights into crop revenues and land, labor, and intermediate input factor demands. All four measures (the first column) are highly skewed to the right with the mean several times of the median. For starters, the sample averages $1,672 in crop revenue per household, almost 2.5 folds of its median with a huge 3,252 standard deviation[6]. Revenue from rice specialization is smaller in both mean ($1,003) and median ($374). On average, households use less than 1 hectare of land for crop growth, the median is only slightly more than half of that. The distribution has a long right tail suggesting most are small farming households. Labor use on farms is between a third and a half of the year at median and mean. Intermediate input use averages $582 a year with a median of $174. For rice crop specialized households, panel B in table 2 reports not only smaller output revenue but in all categories of input use as well due to smaller production

[5] These households are highly specialized in rice production and the sample makes sure output and input observations are untampered with other crops.
[6] I deflate all VND values of 2012, 2014, and 2016 by factors of 1.3451, 1.4607, 1.4741, respectively, and convert all to 2010 US dollar at the exchange rate of $1 = 18,802VND.

scale. Mean land use area is only half compared to the full sample, labor and intermediate input demands are also smaller. To make meaningful comparison between the two sets of samples, next we examine the productivities and factor intensity.

Cross factor ratio (labor/land) reveals that on average, labor-land intensity is comparable between all crops and rice crops, spending 386 days per hectare of land. In the median, rice-specialized households use 100 more labor days per hectare of land than in the full sample, suggesting a slightly more labor-intensive technology for rice farming compared to other crops. Unsurprisingly, labor productivity is higher for rice crops in both mean and median, yielding $0.33-$0.80 more each day of labor than with other crops, earning more than $10.15 in revenue at the mean though only $6 at the median. The picture painted by land productivity is not as straightforward since land returns higher revenue in the mean but less in the median for all crops compared to rice crops, yielding between $2,270-$2,466 per hectare of land a year. Most strikingly, the distribution of returns to intermediate input is almost identical between all household crops and rice crop, yielding 4.62 times in revenue at the mean, 3.4 times at the median, and a 6.5 standard deviation. It is suggestive that intermediate input use is quite robust to crop technologies for the households in the sample.

Figure 1 shows a visual presentation of the dispersion in factor productivities and intensity. In the absence of measurement error, efficient allocation of resources implies that marginal product of factors, which is proportional to crop yield of the corresponding factor, are the same among households in any particular year as they would share the same factor price and face no household-specific distortions. A similar argument can be made about equalized labor-land intensity across households in optimal allocation. Figure 1 reveals a picture far from non-dispersed productivities and cross factor ratios.

The figure plots the distribution of all three factor productivities and labor-land intensity after logarithm transformation using the kernel estimate of the density of the dispersion. In each graph, controls are included for characteristics about households, land quality, and shocks as well as year dummies. Then further geographical controls are added, including regional fixed effects and then narrowing down to commune, and lastly, household fixed effects to account for regional and commune differences and finally the yearly household's deviation.

The same pattern exists in all four graphs and tells the same story. Take the first panel for example. This graph depicts the distribution of land productivity (in logarithm) where dispersion exists in all four specifications but decreases with further controls. Based on the theoretical framework in section 2, these dispersions reveal potential variation in household's shadow prices for land, suggesting the likely market distortions and misallocation of land. The variation appears smaller in more narrow geographical units as price differences become less drastic with a higher level of localization. The variance for logarithm for land productivity after controlling for observable characteristics and year fixed effects is measured at 0.32. Regional differences account for only 4% of that variation, while controlling for smaller geographic units at the commune level accounts for almost 30% of variation. This suggests that while there are regional differences, differences across communes within regions can explain a significantly greater fraction of the market condition heterogeneity. That still leaves more than 70% to be explained by within-commune variation. The household fixed-effects specification addresses changes over time and contains the least amount of dispersion.

Including commune fixed effects eliminates 30% of the variation in measured crop yield per hectare of land, 35% of the variation in measured revenue per labor day, and 29% of the variation in measured output returns per dollar on intermediate input. Productivity of intermediate inputs also displays the least amount of within-commune-year dispersion, reporting a 0.16 variance compared to 0.23 in land productivity and 0.25 in labor productivity. The household-fixed effects specification has the least dispersion with a greatly reduced variance of 0.109 in productivity of intermediate inputs, less than the 0.116 and 0.15 equivalent variances in land and labor, respectively. This suggests that the households face limited changes in market conditions or distortions over time.

These observations motivate the key assumption that there is little change both within a household over time and little within-commune-year variance in the shadow prices as well as elasticities for intermediate inputs, and that most of the observed variance of intermediate input productivity comes from the variation in its measurement error.

The last panel in figure 1 plots the distribution of the logarithm of the labor-land ratio in the data. The cross-factor ratio may be advantageous to output to land size or labor days because it involves only physical measures of land and labor inputs. It mitigates the concern about variations from demand-related factors in production measures. Having said that, the cross-factor ratio reveals a variance even higher (0.164) than that of either land or labor productivity. More variation seems to come from the factor input rather than output, potentially suggesting distortion in the land and labor markets.

These observations are suggestive of factor misallocation, but its extent and the magnitude of potential gains generated from reallocation remain unclear. If measurement error exists, it could be a driving force to introduce dispersion into measured productivities and give a skewed picture of allocative efficiency. Grasping a more accurate understanding of the extent of factor misallocation and its impacts on revenues requires identifying variances of measurement errors.

In what follows, we will lay out the production function estimation and present my key assumption to identify the measurement error variance, and the test for that assumption. After TFP and the variance of measurement errors are estimated, the final step is to measure misallocation and adjust the estimated TFP and potential gains for measurement errors.

4. Estimation

4.1 Production function estimation

Cross-sectional estimation of the production function likely generates inconsistent coefficient estimates since TFP affects household input decisions, while fixed effects is a commonly used approach to control for unobservable time-invariant effects. However, it leaves the estimator susceptible to time-varying factors that the model fails to capture. More importantly, while addressing measurement error, the fixed effects estimation can exacerbate measurement error bias. The fixed effects estimates are reported as a reference point only. Another benchmark reported in the paper is the calculation made with the coefficients used in Ayerst, Brandt, and Restuccia (2020) since their study also investigates factor misallocation in Vietnam using the same dataset[7]. For my own analysis in this paper, the parameters β and the expected factor productivity α_J in equation 1 are estimated using Two-stage least squares (2SLS). The observations are at household level with the full sample and one subsample of households who specialize in rice. The estimation includes year fixed effects and the standard errors are clustered at the commune level.

[7] This paper includes data only from the years 2012, 2014, and 2016, whereas in their paper, earlier rounds of data from 2006, 2008, and 2010 were used as well. However, the coefficients used in Ayerst, Brandt, and Restuccia (2020) were borrowed from the U.S. benchmark rather than estimated.

Output values measured in 2010 US dollar are either the reported rice crop output in the subsample or the aggregate revenue across all crops in the survey in the full sample. Land area and labor supplied by household members used in crop production are available in the survey. Similar to the process performed by Ayerst, Brandt, and Restuccia (2020), we calculated the median of provincial daily wage from a household income and time worked in agriculture outside of household's own farm and used that measure to approximate the amount of hired labor to work on household production. The labor input on the farm is then constructed from the amount of hired labor and self-supplied labor. Intermediate inputs are reported as the aggregate expenditure converted into 2010 US dollars on seeds, saplings, fertilizers, pesticides and herbicides, energy and fuel, maintenance, irrigation and other costs. Covariates used as controls for household observable characteristics are the household head's age, gender, and education level. Land quality controls are aggregated from plot level weighted by their area and include furthest distance of land plot from household, land value, irrigation fraction, fraction of land with land use rights certificates, and perceived land quality compared with commune average (below, average, or above local average). Drought shocks reported by the households are also controlled and allowed to have heterogenous effects on crops depending on land quality through their interactions.

In order to implement the 2SLS estimator, instrumental variables are required to be correlated with the three factor inputs and satisfy the exclusion restriction. The first set of instruments draws from household shocks regarding avian flu, change in commodity price, whether household's head is sick. We argue that these shocks may place a restraint on household's cash and labor available that would affect intermediate input and labor use in crop farming, but otherwise have no direct effect on crop output. Another component of instruments, like the instruments used in Gollin and Udry (2021), involves the interaction between the share of weather shocks (drought) with the share of land of different qualities in the commune outside the household, proxied by the sample data from the commune's other households. It captures the varying effects of droughts on different soil quality. The idea is that having controlled for weather shocks differential impacts based on *household*'s land quality distribution, weather shock effects on the rest of the *commune* bear no direct effect on household' return except through a shadow price change. As such, drought shocks are restricted to only six months out of the survey year so that only droughts that happened early in the crop season would have an impact on input allocation decisions.

Diagnostic tests (under-identification, weak-identification and over-identification tests) are performed and reported at the bottom of table 4 after the results of the second stage estimation. The P-value for the LM-statistic is 0.0047, rejecting the null hypothesis in the under-identification test and suggests that the instruments are indeed relevant and correlated with the endogenous inputs. However, the low Wald F-statistic of 2.916 relative to the critical values at various levels indicates weak instruments. Importantly, the number of instrumental variables allows for the exclusion restriction assumption to be tested. The result indicates that the hull hypothesis that all instruments are valid cannot be rejected, lending confidence to the model specification. The first stage is reported in table A1 in the appendix.

4.2 Identifying variance of measurement errors

The measures observed and recovered in this section are within-household (across year) and within-commune variances. The variation of deviations from the mean is lower than the variation coming from the total sample. Moreover, it allows more room for interpretations[8]. The demean

[8] In Gollin and Udry (2021), the variation from shadow prices would be completely eliminated in the process of taking the deviation from the mean of plots under the same management in the same season. The household-level data does not afford the removal of any source of variation. However, the distribution of mean deviations does allow

transformation is represented in system (4HH) where ˜ represents the deviations from a household's average. Alternatively, in (4C) ˜ denotes the deviations from a commune's yearly average, with an extra subscript c for communes.

$$y_{ht}^{o} = \epsilon_{Yht} + y_{ht} \qquad \rightarrow \qquad \tilde{y}_{ht}^{o} = \tilde{\epsilon}_{Yht} + \tilde{y}_{ht} \tag{4HH}$$

$$j_{ht}^{o} = \epsilon_{Jht} + y_{ht} + \omega_{Jht} + \ln \alpha_J - \ln p_J \qquad \tilde{j}_{ht}^{o} = \tilde{\epsilon}_{Jht} + \tilde{y}_{ht} + \widetilde{\omega}_{Jht}$$

Or expressed in commune's mean deviations:

$$y_{ht}^{o} = \epsilon_{Yht} + y_{ht} \qquad \rightarrow \qquad \tilde{y}_{hct}^{o} = \tilde{\epsilon}_{Yhct} + \tilde{y}_{hct} \tag{4C}$$

$$j_{ht}^{o} = \epsilon_{Jht} + y_{ht} + \omega_{Jht} + \ln \alpha_J - \ln p_J \qquad \tilde{j}_{hct}^{o} = \tilde{\epsilon}_{Jhct} + \tilde{y}_{hct} + \widetilde{\omega}_{Jhct}$$

The key assumption is that there is little change within a household over time or alternatively, little within-commune variance in the shadow prices and elasticities for intermediate inputs. Mathematically, it assumes $\widetilde{\omega}_{Mht} \approx 0$ or $\widetilde{\omega}_{Mhct} \approx 0$. Furthermore, system of equations (5) becomes:

$$\begin{aligned}
&Var(\tilde{y}_{ht}^{o}) = \sigma_{\epsilon Y}^2 + \sigma_Y^2 \\
&Var\left(\tilde{l}_{ht}^{o}\right) = \sigma_{\epsilon L}^2 + \sigma_Y^2 + \ \sigma_L^2 + 2\sigma_{YL} \\
&Var(\tilde{n}_{ht}^{o}) = \sigma_{\epsilon N}^2 + \sigma_Y^2 + \ \sigma_N^2 + 2\sigma_{YN} \\
&Var(\widetilde{m}_{ht}^{o}) = \sigma_{\epsilon M}^2 + \sigma_Y^2 \\
&Cov\left(\tilde{y}_{ht}^{o}, \tilde{l}_{ht}^{o}\right) = \sigma_Y^2 + \sigma_{YL} \approx Cov\left(\tilde{l}_{ht}^{o}, \widetilde{m}_{ht}^{o}\right)
\end{aligned} \tag{5HH}$$

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for a further assumption based on intermediate input use that is important for the identification of measurement error variances.

$$Cov(\tilde{y}^{o}_{ht}, \tilde{n}^{o}_{ht}) = \sigma^2_Y + \sigma_{YN} \approx Cov(\tilde{n}^{o}_{ht}, \tilde{m}^{o}_{ht})$$

The last two equations of (5HH) provide a simple test for the assumption. If the assumption holds and most of that dispersion comes from measurement errors rather the heterogeneity in productivity or shadow price, then $Cov\left(\tilde{y}^{o}_{ht}, \tilde{l}^{o}_{ht}\right) \approx Cov\left(\tilde{l}^{o}_{ht}, \tilde{m}^{o}_{ht}\right)$ and $Cov(\tilde{y}^{o}_{ht}, \tilde{n}^{o}_{ht}) \approx Cov(\tilde{n}^{o}_{ht}, \tilde{m}^{o}_{ht})$. That is the observed intermediate inputs are expected to covary with the other observed factor demands similarly to how measured output covary with them. On the contrary, if the assumption does not hold, and there are a lot of changes in technology, factor quality, and market conditions within a household over the years, those changes would covary with land in a different way from output.

Observations from figure 1 and table 2 motivated the assumption. It is now time to turn to more concrete evidence from the data. Table 3 reports on variances and covariances of observables. In panel A, the differences $Cov\left(\tilde{y}^{o}_{ht}, \tilde{l}^{o}_{ht}\right) - Cov\left(\tilde{l}^{o}_{ht}, \tilde{m}^{o}_{ht}\right)$ and $Cov(\tilde{y}^{o}_{ht}, \tilde{n}^{o}_{ht}) - Cov(\tilde{n}^{o}_{ht}, \tilde{m}^{o}_{ht})$ are very close to 0. There are the most striking differences in the rice sample between the covariances with labor, and even here the differences are only around 0.01. These observations further strengthen the argument for little heterogeneity in market and productivity conditions for intermediate inputs and lend support to this key identification assumption.

Under (5HH), not every variance is identifiable. The solvable variables are variances of measurement error in output and intermediate input $(\sigma^2_{\epsilon Y}, \sigma^2_{\epsilon M})$, variance of true production output and variances of land and labor productivities-distortions $(\sigma^2_Y, \sigma^2_L, \sigma^2_N)$, and the covariance between land and labor productivities-distortions (σ_{LN}). The two variances of measurement error in land and labor $(\sigma^2_{\epsilon L}, \sigma^2_{\epsilon N})$ remain unidentifiable.

This estimate of measurement error variance provides a lower bound for the overall variance of measurement error. Adjusting for within-household variance instead of total sample variance coupled with under-identification ensures that misallocation is not over-adjusted for measurement error.

4.3 Misallocation gap and adjustment

Household TFP is estimated by the production residuals. Applying the TFP and coefficient estimates to the optimal household's allocation share $s_h = \frac{\exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}{\sum_h \exp\left(\frac{\omega_{Yh}}{1-\sum_J \alpha_J}\right)}$ provides the complete estimates of all households' efficient allocation and production as well as potential gains from reallocation before adjustment for measurement error. The estimate for the variance of TFP is adjusted using equation (2) by subtracting from its variance the within-commune or within-household variance of aggregate measurement error $\widehat{Var}(\epsilon_{ht}) = \hat{\sigma}^2_{\epsilon Y} + \hat{\alpha}^2_M \hat{\sigma}^2_{\epsilon M}$. The potential gain from reallocating factors can also be adjusted using equation (3).

5. Results

5.1. Production Function Estimation

The production estimates are presented in table 4. For comparison, column 1 reports the coefficients of land, labor, and intermediate input used in Ayerst, Brandt, and Restuccia (2020) paper, column 2 is the household fixed-effects results, and column 3 reports my preferred 2SLS estimates for the whole sample. The first stage is reported in table 1 of the appendix. The land, labor, and intermediate input coefficients are estimated to be 0.42, 0.19 and 0.33. Compared to

ABR [9] and fixed-effects specifications, the 2SLS estimates are closer to constant returns to scale. Land accounts for a relatively higher share of revenue using 2SLS, whereas the share of intermediate inputs is comparable across the two models.

Land value and self-reported relative land quality prove to be good indicators of land quality, which show statistically significant positive correlations with revenue even if modest in magnitude. Particularly, doubling the value of land leads to a 1.4% increase in revenue, which translates into a $9.4 increase in median crop value. Drought weather shocks negatively affect crop revenues. The coefficients of demographic controls are not surprising but not significant. Households with older or higher-educated heads receive higher crop revenue, whereas female heads tend to have lower yields.

5.2. TFP dispersion and its relationship with output and inputs

Production estimation provides estimates for the unadjusted logarithm of TFPs using production residuals. In a distortion-free environment, TFP would have a strong positive correlation with all inputs and hence revenue as well. The more friction is introduced into factor and output markets, the weaker this relationship becomes; and in extreme cases, the direction could turn negative in instances where distortions are severe, which prevent more productive households from acquiring more inputs. Examining how TFP correlates with factor inputs and revenue can provide insight into the allocative efficiency of the factor markets. Insights can be gained even when TFP estimates are confounded by measurement errors as long as true productivities and measurement errors are orthogonal. Figure 2 features four graphs depicting the relationships and linear fits between the log TFP estimates (with 1% trimmed at the top and bottom) and inputs and revenue. In all four

[9] The paper makes many references to Ayerst, Brandt, and Restuccia (2020) , which will be shortened as ABR for convenience.

panels, productivity shows the strongest positive association with revenue with a 0.8 correlation and a 0.6 correlation with intermediate inputs. The relationship with land and labor is still positive, but the correlation is found to be around 0.3 The pattern remains the same in figure 3 in rice production. This suggests distortion in the land labor markets. This observation is of little surprise in the presence of, among other things, crop regulations where certain plots of land are restricted to rice growth to ensure food security. However, intermediate input use is found to be relatively efficient.

Table 5 reports on the dispersion of productivity, including the variance of log and the 90th-10th percentile log difference after trimming the top and bottom 1% of the residual prediction. ABR's coefficients while controlling for no other observable characteristics understandably result in the most dispersed TFP with a 0.28 log variance and a 1.26 difference between the 90^{th} and 10^{th} percentiles. When demographics, shocks, and input qualities are taken into account, the dispersion drops significantly. With full crops, both FE and 2SLS estimates report similar variances at 0.16 and 0.14 respectively, which is about half that using ABR.

5.3. Calibrating Measurement Errors and True Output/Input variances

We now move on to calculating the measurement error induced variance within the raw TFP estimate. As noted in Section 4, the system of equations in my approach is not identified with the assumptions made. We are only able to solve for variance of measurement error in output revenue and intermediate inputs. Table 6 documents the solutions to identifiable variables, which also include variance of output productivity, covariance of output and land productivities, covariance of output and labor productivities, and covariance of land and labor productivities. Panel A is similar to a household fixed effects approach where household's data is demeaned by their average across years while panel B uses data points demeaned by year-commune average while.

The majority of dispersion in observed outputs is caused by actual output variation rather than measurement error, and there seems to be more variation in productivity in the south than the north. Within-household true output variance across years is 0.14 in the country, 0.11 in the north and 0.18 in the south in the full sample of households regardless of crops. This holds true for the restricted sample of rice-exclusive farming households as well, to a lesser magnitude, with variances of 0.08, 0.07, and 0.1 in the nation, north and south regions, respectively. The decrease in the spread of true output productivity nationwide and both regions suggests a more homogeneous set of rice-exclusive farming households in terms of productivity. The covariances results indicate that land and labor specific productivities are positively correlated and are each negatively correlated with true output. One interpretation is that land and labor use efficiency are complementary rather than supplementary, the better households can make use of land the better they can make use of labor. Furthermore, constraints in one factor market could be positively linked with that in the other factor market as well.

My measurement error variance results indicate that there are rather large dispersions in measurement error of intermediate inputs relative to the measurement error of output. For example, we found 0.12 a within-household variance in intermediate input measurement error in the full sample, 0.15 in the north and 0.1 in the south. In the rice-crop restricted sample, these variances are even higher, 0.24 in the nation, 0.2 in the north, and 0.27 in the south. Compared to that, the within-household variances in output measurement error are a few times smaller in the modest range of 0.02-0.04. Indeed, considering the diverse items reported in the survey under the category of intermediate input, it is reasonable that there be more variation in measurement error of intermediate inputs. Measurement error in intermediate inputs is weighted by the square of its output elasticity, which is a range of 0.11-0.15. Measurement errors in land and labor are unidentified, leaving the aggregate measurement error variance estimate most likely under-computed. Panel B reports the same findings using within commune-year variances. As expected, we find much less within-household true output variation, since most of it comes from year-to-year shocks and may be price distortion differences, rather than actual households' factor use efficiency. There is barely any variation at all when we examine rice growers only.

5.4. Measurement Error and Reallocation gains

Table 7 combines the findings of TFP from table 5 and measurement error from table 6. After the estimates of the raw log TFP and measurement error variance are obtained, the next investigation is to learn how much measurement error in aggregate confounds the true TFP and calculate output gains from reallocating before and after adjustment for confoundment. In table 7, we again report two panels for two sets of estimates, within households across years in panel A, and years within commune-year in panel B.

The unadjusted log TFP estimates are the residuals from the production function, its variance report is repeated from table 5. The adjusted variance of log TFP is simply the difference between unadjusted log TFP and measurement error variances. Aggregate measurement error variance is the weighted sum of variances of output and intermediate input measurement errors.

Between the within-household and within-commune variances, measurement error variance is calculated to be between 0.04 and 0.06, accounting for 30-45% of TFP variance. Based on these findings, the country could more than double its crop output by reallocating. While this is not uncommon, this magnitude is more often seen in African agriculture such as a 186% increase in

Uganda (Aragon, Restuccia, and Rud, 2021), and 259% in Malawi (Chen, Restuccia, and Santaeulàlia-Llopis 2023), and is far from what is seen for Vietnam's neighbor China with an increase of 53% (Adamopoulos et al., 2022). This adds to the evidence that allocative inefficiency may be overstated by raw TFP estimates.

Using ABR's coefficients and calculated output gains for benchmark and found only a 79% potential increase. This difference is neither surprising nor does it speak to which estimate is closer to the truth. Rather the estimates offer a possible range and point out room for improvement. The set of coefficients estimated in this paper using 2SLS translates into a distribution of TFP, 30-45% of whose variation is confounded by measurement errors, while ABR's coefficients estimate that only15-22% of TFP variation is measurement error induced. The adjustment for measurement error reduces all estimates of potential gains from reallocation. After adjustment, the 2SLS method estimates a much more modest 45-72% allocative efficiency gain, and the ABR ranges from 58%-65% potential gain. Depending on the set of coefficients and measurement error adjustment method/assumption, we find that the gains through factor reallocation are overestimated up to threefold in the national sample of households.

Both methods of adjustment using within-household variances and within-commune variances are found to perform consistently and yield simila results.

5.5. Heterogeneity analysis results

The TFP variance from rice production is drastically smaller, suggesting the rice specialists constitute a more homogeneous selection of farmers. Measurement error from the rice production is consistently responsible for a higher fraction of the TFP than from the aggregate crop production, with one exception (the within commune-year variances). This potentially suggests that the aggregation method does seem to have power against the impact of measurement error.

The historical and natural differences between the two regions translate into large differences in agricultural practices and efficiency. Both regions specialize in rice crops but the South is a larger rice producer by far. The comparative analysis between the North and the South examines their respective efficiency.

Regionally, the raw TFP has higher dispersion in the Southern sample than the Northern sample in the aggregate production. The unadjusted estimate of potential gains from reallocation is large in both regions for aggregate crops, more than doubling productions (131% and 123% in North and South, respectively). Unsurprisingly, efficiency is higher in rice production with smaller predicted gains from allocation; however, the potential gains are still estimated to be more than half of current production (66% and 59% in North and South, respectively). In both productions, the unadjusted estimates find the South to be more efficient in resource allocation.

After adjusting for measurement error, the allocative gain estimate is drastically reduced in both regions and both crop productions. The gains from reallocation of resources within each region are estimated in the 32%-51% range for all crops. However, a different pattern emerges. The North is subject to such large variation in measurement error that after adjustment, the region seems to gain a slight edge in the overall production, and the edge is higher using within-commune variance estimates. This finding is surprising and calls for a closer examination of the agricultural practices and conditions in the two regions. On the other hand, not only is rice crop confirmed to be the comparative advantage of the South in rice production, but the adjusted measures find that the South is greatly efficient at allocating resources in rice growing that reallocation can only increase production by 15% of production.

5.5. Crop-level analysis

In this section, we replicate Gollin and Udry (2021) method and assumptions for identification. The results are included in the appendix. The structure of household survey data used in this study is not suited for a highly demanding plot-level data approach. The lack of seasonal and plot-level input information prevents the analysis to be performed at this level. Thus we divided crops into three categories: rice, maize, and all other crops, as output and input observations are available in the available dataset for these categories. The drawback of this procedure is that additional dispersion is being added rather than removed from the production residuals, stemming from crop technology heterogeneity, inherent factor quality requirement differences, varying seasons and timing within a year, etc. It is for these reasons that the results of this exercise should not be taken literally.

Table A3 summarizes the observed variances and covariances of observed outputs and inputs deviation from the household-year average. A quick look reveals nonnegligible differences between how output and intermediate inputs covary with land and labor, suggesting non-trivial variation in true intermediate input use across households' different crops, which invalidates my assumption on intermediate inputs.

Another concern of this approach is that since there can be multiple seasons growing different crops within any year, the sum of land use often far exceeds the total amount of land available to farmers. This creates a challenge in computing the output loss from misallocation since any plot of land can be counted multiple times if it is used repeatedly and spread across different categories of crops.

For the sake of the exercise, consider each year a single point in time, and the amount of land available is the sum of area every time it is used. Every household has its own ratio of self-reported land use for crops over landholdings, where the median of this distribution is 2, with a 2.07 mean and 3.6 at 90th percentile. If we simply total every household's self-reported land use at crop level, the sum is 1.6 times every household's landholding. Gains from reallocating are calculated and reported using these four values. The higher land availability is assumed, the larger the output gap.

Table A4 shows that within the 0.39 variance of unadjusted log TFP from the set of IV coefficient estimates, measurement error causes 63.2% of that dispersion. Even in the most conservative estimate, the raw gain from reallocation comes at an unrealistic 548%, and becomes an outlandish 815% in the more liberal assumption. After removing the 63% share of measurement error from log TFP variance, the gap is drastically adjusted down to anywhere from less than 1% to a seemingly reasonable 42%. It also means that the output gap is being exaggerated from 19 times to over 900 times. These estimates should not be taken literally for the many reasons discussed above, but they showcase once again how measurement error can lead to a severe overstatement of misallocation gap.

6. Conclusion

Resource misallocation in the agricultural sector is the main cause of productivity and income differences across nations and regions and there are a large number of existing studies exploring the determinants and consequences of resource misallocation in the agricultural sector (Caselli 2005; Restuccia, Yang, and Zhu 2008; Restuccia and Rogerson 2017). However, few have seriously taken the measurement errors of output and inputs into account in their estimations of the productivity costs of resource misallocation despite the fact that measurement errors are known to be prevalent in developing countries. As a result, the costs of resource misallocation are likely to be overestimated because part of the estimated effects are indeed associated with measurement errors. Gollin and Udry (2021) is the first study developing approaches to decompose the causes of productivity gaps in the agricultural sector into a part that is truly due to resource misallocation and a part associated with measurement errors. They found that failing to account for misallocation would substantially overestimate the productivity costs of misallocation.

Despite the difference in data structure and different empirical strategies, this study largely confirms the findings of recent studies (Gollin and Udry 2021, Aragon, Restuccia, and Rud 2021) that measurement error plays a substantial role in the estimation of productivity effects of resource allocation. More specifically, failing to account for measurement error associated with output and inputs would lead to a large overestimation of the negative effects of resource misallocation on productivity. Further analysis shows that misallocation varies across regions where the property rights and market conditions are historically quite different. These findings further highlight the importance of taking the measurement errors into account for future studies quantifying misallocation and productivity inefficiency.

The paper is limited in several ways. The assumption of classical measurement error may be too restrictive given the emerging evidence of non-classical measurement error (Desiere and Jolliffe 2018; Abay et al. 2019; Abay 2020; Ayalew et al. 2024)[10]. The method in this paper only allows for the identification of within-household and within-commune variances rather than the overall variances; additionally, measurement errors in land and labor are unidentified, leading to an underestimation of measurement error impact. The variances of two factor inputs, land and labor,

[10] Like Bils, Klenow, and Ruane (2021) and Gollin and Udry (2021), measurement error is necessarily assumed to be classical for identification in the paper. Furthermore, studies on non-classical measurement error find that they tend to correlate with extreme farm sizes. A highly homogeneous society, farm size and farming practices are less likely to be dichotomous in Vietnam, lending some support to the classical measurement error assumption.

cannot be identified, and the recovered measurement error variances are within-household and within-commune, rather than total sample variance. Nevertheless, the conservative estimates significantly lower the risk of overadjustment.

This paper makes several contributions. It is an entry to the thin literature on the impact of measurement error on misallocation and the first to do so for Vietnam. The method developed in the paper is adaptable to household survey data in similar contexts, saving costs on high-quality data. The paper proposes a key assumption on intermediate input use that allows for testing and identification of the variance of measurement error. The addition of intermediate inputs is essential in this context since Vietnam is within the region with the highest consumption. The method contributes by not only adding intermediate inputs into the production function but also using it as a key identification instrument. The use of household-level data to address measurement error is cost-effective and may even be advantageous over plot-level data if measurement error can be aggregated out (Aragon, Restuccia, and Rud 2021). Finally, the regional differences in allocative efficiency between the North and the South are highlighted, drawing attention to the differential needs of the two agricultural economies.

The paper finds that measurement error accounts for 30%-45% of the variation in TFP, and failing to address the measurement error leads to doubling and tripling the estimated gains from reallocation. This study suggests that after adjustment for measurement errors, potential gains from reallocation are drastically lowered and range from 46% to 71%. Given the significant impact of measurement error on the estimate of gains from reallocation, researchers and policymakers should exercise caution when interpreting measures of potential gains from reallocation, especially when comparing them with the often large costs of reallocation.

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Figure 1: Distribution of factor productivities and labor/land ratio, controlling for observable characteristics with top and bottom 1% trimmed

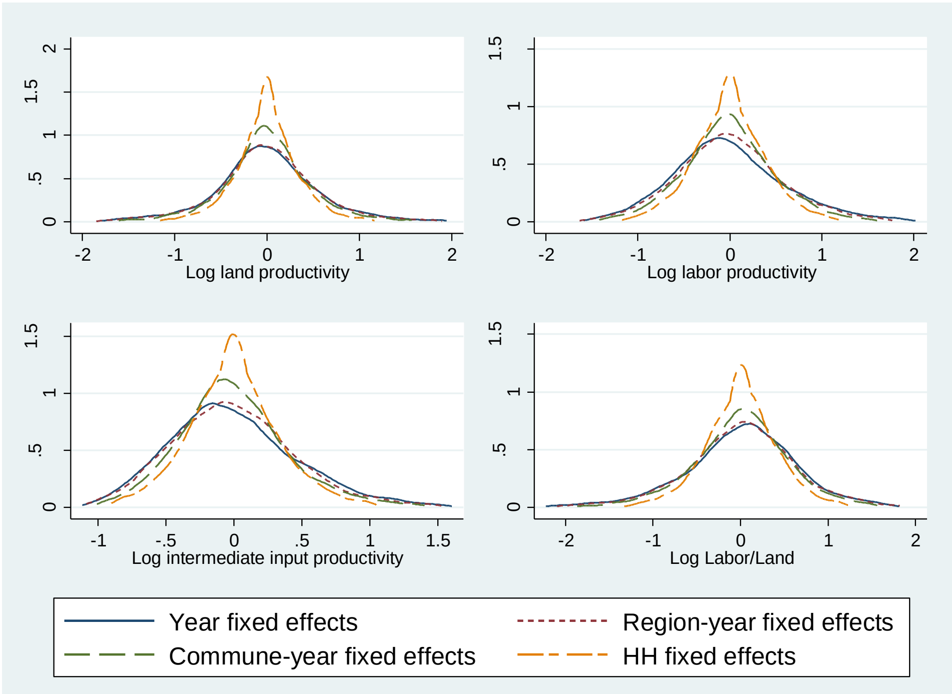

Figure 2: Output, Input and unadjusted log TFP in all crop sample

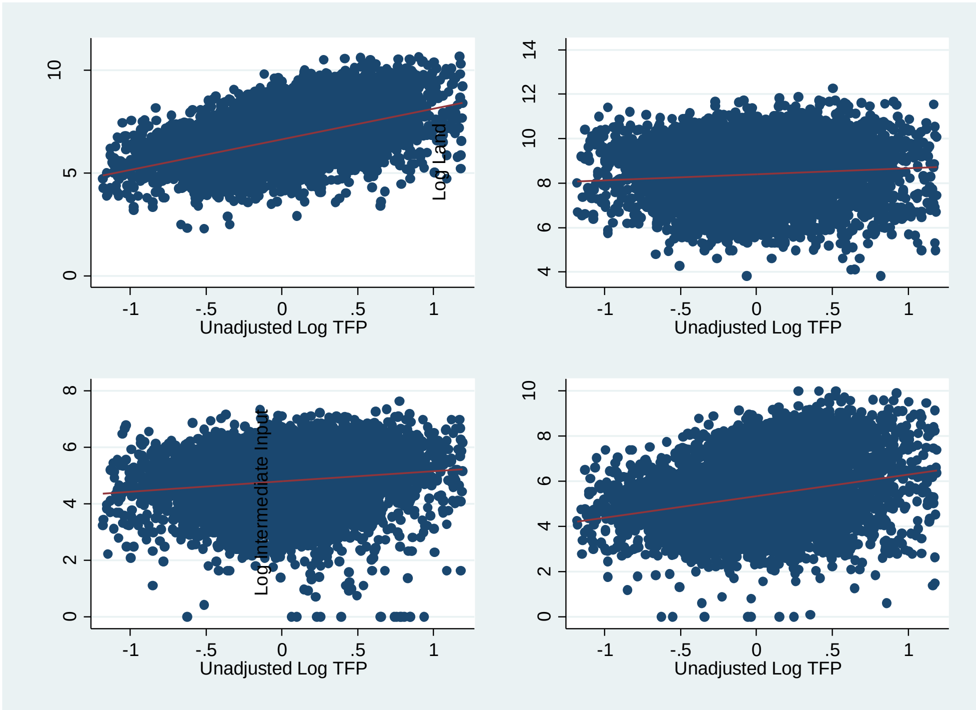

Figure 3: Output, Input and unadjusted log TFP in sole rice farming households

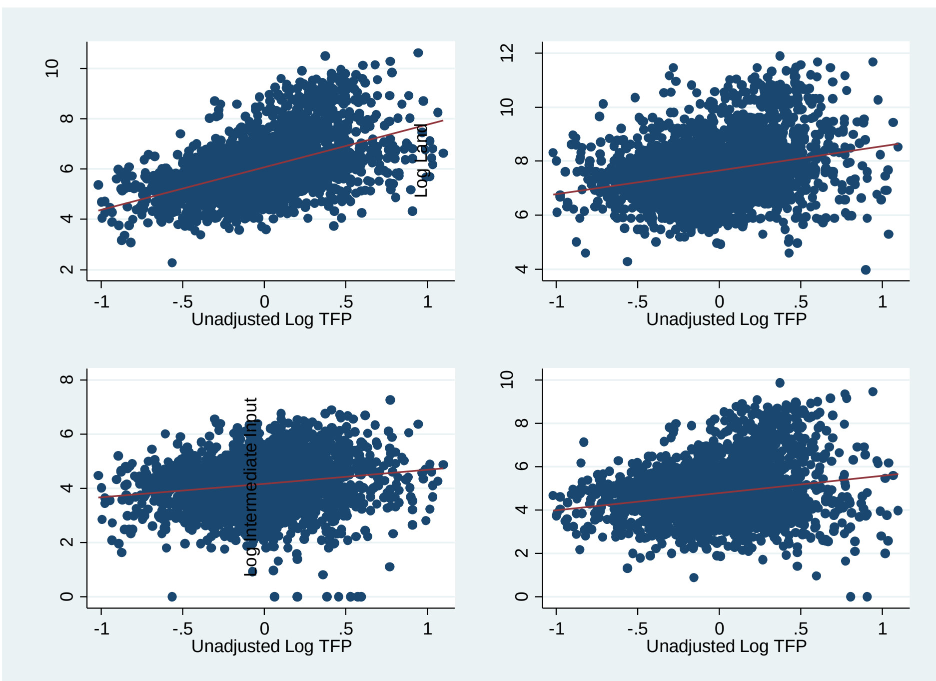

Table 1: Sample

Sample size	Pooled	2012	2014	2016
Household-years	8264	2887	2861	2516
Households	3140	2887	2861	2516
Communes	492	481	464	456
Districts	138	138	136	135
Provinces	12	12	12	12
Mean Crops/Household-years	2.11	2.12	2.14	2.06

Source: VARHS by UNU WIDER. Statistics are calculated by the author.

Table 2: Output, inputs, and factor productivities

A. All crops				*B. Rice only HH*			
Output ($)		Labor/Land (Days/ha)		Output ($)		Labor/Land (Days/ha)	
Mean	1672.36	Mean	385.13	Mean	1003.31	Mean	386.29
Median	672.09	Median	271.07	Median	374.053	Median	337.06
STD	3252.15	STD	573.63	STD	2441.94	STD	306.17
Land Area (ha)		Land productivity ($/ha)		Land Area (ha)		Land productivity ($/ha)	
Mean	0.8915	Mean	2466.45	Mean	0.4796	Mean	2270.04
Median	0.47	Median	1981.6	Median	0.19	Median	2216.7
STD	1.5238	STD	3748.18	STD	1.0458	STD	1693.19
Labor (days)		Labor productivity ($/Day)		Labor (days)		Labor productivity ($/Day)	
Mean	175.69	Mean	9.35	Mean	131.78	Mean	10.15
Median	130	Median	5.67	Median	84	Median	6
STD	162.93	STD	18.71	STD	149	STD	19.69
Intermediate input ($)		Interm. input productivity		Intermediate input ($)		Interm. input productivity	
Mean	581.93	Mean	4.62	Mean	343.83	Mean	4.62
Median	173.94	Median	3.37	Median	102.81	Median	3.38
STD	1327.24	STD	6.46	STD	966.73	STD	6.47

Source: VARHS by UNU WIDER. Statistics are calculated by the author.

Table 3: Variances and Covariances of observed outputs and inputs

	All crops			Rice only HH		
	Nation	North Region	Southern Region	Nation	North Region	Southern Region
A. Within HH across year						
Var(Output)	0.1745	0.1459	0.2215	0.1113	0.0901	0.1321
Var(Land)	0.1107	0.1167	0.1008	0.0921	0.0886	0.0957
Var(Labor)	0.2257	0.2162	0.2413	0.2286	0.1979	0.2588
Var(Interm. Input)	0.2636	0.2553	0.2774	0.3186	0.2695	0.3667
Cov(Output, Land)	0.0506	0.0511	0.0499	0.0573	0.0538	0.0606
Cov(Output, Labor)	0.0851	0.0794	0.0946	0.0577	0.0552	0.0603
Cov(Output, Interm. Input)	0.1389	0.112	0.1833	0.0823	0.0662	0.098
Cov(Land, Labor)	0.0406	0.0462	0.0315	0.0459	0.0536	0.0383
Cov(Land, Interm. Input)	0.0463	0.0411	0.0549	0.0536	0.0514	0.0559
Cov(Labor, Interm. Input)	0.0831	0.072	0.1015	0.0696	0.0604	0.0786
Cov(Output, Land) - Cov(Land, Interm. Input)	-0.0043	-0.01	0.005	-0.0037	-0.0024	-0.0047
Cov(Output, Labor) - Cov(Labor, Interm. Input)	-0.002	-0.0074	0.0069	0.0119	0.0052	0.0183
B. Within commune-year						
Var(Output)	0.5663	0.4063	0.8286	0.4125	0.293	0.5383
Var(Land)	0.5486	0.4563	0.6999	0.4382	0.3222	0.5604
Var(Labor)	0.4533	0.3872	0.5617	0.4569	0.399	0.5181
Var(Interm. Input)	0.6516	0.4728	0.9444	0.6737	0.4961	0.8606
Cov(Output, Land)	0.3925	0.2973	0.5486	0.3712	0.2638	0.4843
Cov(Output, Labor)	0.3584	0.28	0.4868	0.2986	0.2313	0.3694
Cov(Output, Interm. Input)	0.5151	0.3468	0.7908	0.3896	0.275	0.5102
Cov(Land, Labor)	0.3173	0.2592	0.4125	0.304	0.2404	0.371
Cov(Land, Interm. Input)	0.3898	0.2878	0.5568	0.3721	0.2634	0.4865
Cov(Labor, Interm. Input)	0.3589	0.2735	0.4988	0.3121	0.2428	0.3852
Cov(Output, Land) - Cov(Land, Interm. Input)	-0.0027	-0.0095	0.0082	0.0009	-0.0004	0.0022
Cov(Output, Labor) - Cov(Labor, Interm. Input)	0.0005	-0.0065	0.012	0.0135	0.0115	0.0158

Table 4: Production Function

	ABR	FE	2SLS
Land in m2 (Log)	0.2	0.225***	0.420***
		(0.0213)	(0.114)
Labor (Log)	0.3	0.178***	0.190*
		(0.0162)	(0.107)
Intermediate input (Log)	0.3	0.429***	0.328***
		(0.0185)	(0.113)
Year = 2014		-0.0169	-0.0121
		(0.0167)	(0.0407)
Year = 2016		0.0335	-0.0196
		(0.0209)	(0.0366)
Head's age		0.00171	0.000751
		(0.00146)	(0.000708)
Female head		-0.0184	-0.0498
		(0.0447)	(0.0496)
Head's education		0.0168	0.0446*
		(0.0125)	(0.0248)
Furthest distance from land (Log)		0.000185	-0.0202
		(0.00832)	(0.0237)
Land value (Log)		0.000385	0.0213**
		(0.00240)	(0.00916)
Irrigated fraction		0.0123	0.473***
		(0.0360)	(0.172)
LURC fraction		0.0199	0.0680
		(0.0255)	(0.0422)
Crop restricted fraction		0.0444**	-0.160
		(0.0218)	(0.120)
Below average land quality		-0.0492**	-0.0734**
		(0.0207)	(0.0297)
Average land quality		-0.0188	0.0189
		(0.0298)	(0.0374)
Above average land quality		0.0190	0.0952***
		(0.0290)	(0.0362)
Missing land quality		-0.000401	-0.115
		(0.196)	(0.127)
Drought		-0.0858	-0.150
		(0.103)	(0.115)
Drought x Below average land quality		-0.0128	0.0495
		(0.0689)	(0.0663)

Drought x Average land quality	0.0733	0.101
	(0.0935)	(0.109)
Drought x Above average land quality	0.0260	0.104
	(0.145)	(0.195)
Constant	1.473***	0.246
	(0.164)	(0.983)
Observations	8,233	8,032
R-squared	0.500	0.831
Number of hhid	3,146	
Under-identification test		
Kleibergen-Paap rk LM-statistic		15.01
$\chi^2(4)$ P-value		0.0047
Weak identification test		
Cragg-Donald Wald F-statistic		3.527
Kleibergen-Paap rk Wald F-statistic		2.916
Stock-Yogo weak ID test critical values		
5% maximal IV relative bias		12.20
10% maximal IV relative bias		7.77
20% maximal IV relative bias		5.35
30% maximal IV relative bias		4.4
Over-identification test of all instruments		
Hansen J-statistic		6.182
$\chi^2(3)$ P-value		0.1031

Note: Standard errors are clustered at the commune level. Robust standard errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Unadjusted TFP

	All crops		Rice crop	
	Variance of log	90-10 log difference	Variance of log	90-10 log difference
ABR	0.28	1.26	-	-
FE	0.16	1.04	-	-
IV				
Nation	0.14	0.94	0.10	0.79
Northern Region	0.11	0.84	0.10	0.75
Southern Region	0.18	1.03	0.11	0.84

Table 6: Estimates of variances and covariances of measurement error and productivity

	All crops			Rice only HH		
	Nation	North Region	Southern Region	Nation	North Region	Southern Region
A. Within HH across years						
Output ME	0.03	0.04	0.04	0.03	0.02	0.03
Interm. Input ME	0.12	0.15	0.1	0.24	0.2	0.27
True output	0.14	0.11	0.18	0.08	0.07	0.1
Total and land productivities	-0.09	-0.06	-0.13	-0.02	-0.02	-0.04
Total and labor productivities	-0.05	-0.03	-0.09	-0.02	-0.01	-0.04
Land and labor productivities	0.04	0.03	0.07	0.01	0.01	0.02
B. Within commune-year						
Output ME	0.05	0.06	0.04	0.02	0.01	0.03
Interm. Input ME	0.13	0.12	0.15	0.28	0.22	0.35
True output	0.52	0.35	0.79	0.39	0.28	0.51
Total and land productivities	-0.13	-0.05	-0.24	-0.02	-0.02	-0.03
Total and labor productivities	-0.16	-0.05	-0.2	-0.09	-0.05	-0.14
Land and labor productivities	0.09	0.05	0.16	0.02	0.03	0.03

Table 7: Log TFP adjustment and allocative gains

	All crops			Rice only HH		
	Nation	North Region	Southern Region	Nation	North Region	Southern Region
A. Within HH across years						
Unadjusted log TFP	0.14	0.11	0.18	0.10	0.10	0.11
Adjusted log TFP	0.10	0.06	0.13	0.04	0.04	0.04
ME	0.04	0.06	0.05	0.07	0.05	0.07
Share of ME in unadj log TFP	30.1%	49.3%	28.7%	64.5%	53.1%	63.6%
Unadjusted gains	138.9%	131.1%	122.9%	63.5%	66.4%	58.5%
Adjusted gains	71.6%	49.9%	50.7%	26.8%	37.3%	20.8%
Unadj.gains / Adj. gains	1.94	2.63	2.42	2.37	1.78	2.81
B. Within commune-year						
Unadjusted log TFP	0.14	0.11	0.18	0.10	0.10	0.11
Adjusted log TFP	0.08	0.04	0.12	0.04	0.05	0.03
ME	0.06	0.07	0.06	0.06	0.04	0.08
Share of ME in unadj log TFP	44.8%	64.1%	31.8%	60.8%	45.8%	74.5%
Unadjusted gains	138.9%	131.1%	122.9%	63.5%	66.4%	58.5%
Adjusted gains	45.9%	31.7%	44.6%	28.7%	40.9%	15.3%
Unadj.gains / Adj. gains	3.03	4.13	2.76	2.21	1.62	3.81

Table 7 (cont.): Log TFP adjustment and reallocating gains

	ABR	FE
A. Within HH across year		
Unadjusted log TFP	0.28	0.16
Adjusted log TFP	0.24	0.11
ME	0.04	0.05
Share of ME in log TFP	14.5%	31.8%
Unadjusted gains	78.6%	55.7%
Adjusted gains	64.6%	37.8%
Unadj.gains / Adj. gains	1.22	1.47

	ABR	FE
B. Within commune-year		
Unadjusted log TFP	0.28	0.16
Adjusted log TFP	0.22	0.09
ME	0.06	0.07
Share of ME in log TFP	21.9%	45.1%
Unadjusted gains	78.6%	55.7%
Adjusted gains	57.8%	30.9%
Unadj.gains / Adj. gains	1.36	1.80

Appendix

A1. First stage of all crop production

	Land	Labor	Intermediate Input
Drought x Commune's below average land quality	-0.239	0.254	0.424*
	(0.203)	(0.174)	(0.246)
Drought x Commune's average land quality	0.132	0.0685	0.276*
	(0.122)	(0.106)	(0.161)
Drought x Commune's above average land	0.520	0.694	0.772
	(0.740)	(0.708)	(0.731)
Avian flu	0.0730	0.149***	0.00643
	(0.0467)	(0.0381)	(0.0540)
Change in other commodity prices	-0.0724	0.267***	-0.000883
	(0.0795)	(0.0703)	(0.0900)
Shock from illness or death	0.0268	0.0689	-0.00166
	(0.0770)	(0.0603)	(0.0838)
Head was sick	-0.129***	-0.0792**	-0.0958**
	(0.0411)	(0.0327)	(0.0479)
year = 2014	-0.0258	-0.205***	0.120***
	(0.0174)	(0.0195)	(0.0252)
year = 2016	0.0765***	-0.154***	0.0621*
	(0.0249)	(0.0251)	(0.0326)
Head's age	-0.00727***	-0.00350***	-0.00777***
	(0.00154)	(0.00119)	(0.00185)
Female head	-0.435***	-0.370***	-0.412***
	(0.0507)	(0.0395)	(0.0613)
Head's education	-0.157***	-0.0885***	-0.0137
	(0.0199)	(0.0148)	(0.0238)
Furthest distance from land (Log)	0.173***	0.116***	0.0825***
	(0.0153)	(0.0107)	(0.0162)
Land value (Log)	0.0408***	0.0235***	0.0827***
	(0.00528)	(0.00400)	(0.00638)
Irrigated fraction	-0.390***	0.107***	1.043***
	(0.0483)	(0.0389)	(0.0646)
LURC fraction	-0.0710*	-0.0506*	0.251***
	(0.0389)	(0.0301)	(0.0474)
Crop restricted fraction	-0.743***	-0.304***	-0.778***
	(0.0388)	(0.0303)	(0.0466)

Below average land quality	0.0639	-0.0288	-0.103**
	(0.0430)	(0.0371)	(0.0513)
Average land quality	0.211***	0.228***	0.218***
	(0.0605)	(0.0516)	(0.0725)
Above average land quality	0.169**	0.208***	0.300***
	(0.0673)	(0.0558)	(0.0807)
Missing average land quality	-0.140**	-0.0577	-0.178
	(0.0619)	(0.153)	(0.269)
Drought x Household's below average land quality	0.0307	0.175***	0.236***
	(0.0683)	(0.0598)	(0.0872)
Drought x Household's average land quality	0.190***	0.234***	0.282***
	(0.0346)	(0.0299)	(0.0417)
Drought x Household's above average land	-0.306**	-0.0454	0.0232
	(0.136)	(0.113)	(0.175)
Drought x Household's missing average land	0.283***	0.338	-0.213
quality	(0.0940)	(0.230)	(0.373)
Constant	7.896***	4.085***	7.110***
	(0.176)	(0.130)	(0.198)
Observations	6,474	6,474	6,474

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A2. Variances and Covariances of observed crop outputs and inputs *within HH-year across crops*

Var(Output)	0.8459
Var(Land)	0.7727
Var(Labor)	0.6304
Var(Interm. Input)	1.3592
Cov(Output, Land)	0.5645
Cov(Output, Labor)	0.5527
Cov(Output, Interm. Input)	0.826
Cov(Land, Labor)	0.3927
Cov(Land, Interm. Input)	0.6607
Cov(Labor, Interm. Input)	0.6583

A3. Estimates of variances and covariances of measurement error and productivity *within HH-year across crops*

Output ME	0.2
Land ME	0.14
Labor ME	0.03
Interm. Input ME	0.19
True output	0.65
Land productivity	0.16
Labor productivity	0.15
Interm. Input productivity	0.16
Total and land productivities	-0.09
Total and labor productivities	-0.1
Total and Interm. Input productivities	0.18
Land and labor productivities	-0.07
Land and Interm. Input productivities	-0.08
Labor and Interm. Input productivities	-0.07

A4. Log TFP adjustment and allocative gain estimates at crop level based on land use efficiency

C. Within HH-year (Crop level)	Min (1.6)[11]	50th percentile (2)	Mean (2.07)	90th percentile (3.6)
Unadjusted log TFP			0.39	
Adjusted log TFP			0.14	
ME			0.25	
Share of ME in log TFP			63.2%	
Unadjusted gains	548.1%	614.6%	625.1%	814.8%
Adjusted gains	0.6%	11.0%	12.6%	42.0%
Ratio of unadj. and adj. gains	913.50	56.03	49.69	19.38

[11] These numbers represent the ratio of land use over landholdings.