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Economic efficiency versus social equity: The productivity challenge for rice production in a 'greying' rural Vietnam

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ABSTRACT

Increasing agricultural productivity is often deemed necessary to enhance rural income and ultimately narrow the urban–rural disparity in transitional economies. However, the objectives of social equity and economic efficiency can contradict each other, especially in the context of fierce competition for resources between agriculture and non-agricultural sectors and given the inherently and largely redundant and unskilled aging rural population that often occurs during the economic transition to a market economy. We investigate the case of Vietnam during its high growth period (2000–2016), over which the country introduced policies to increase efficiency in rice production and income for farmers. Contrary to expectations, we find a substantial fall in the terms of trade for rice, indicating a regression in farm income. This fall in the terms of trade did not enhance technical change, as seen in other countries, and only marginally improved technical efficiency in most regions. The reason stems from Vietnam's limited investment in scientific research and development and policies that restrict farmers' decision-making power in production, among others. We further examine the causes of inefficiency using data from two household surveys in 2004 and 2014 (with plot-level information) and semi-structured interviews with farmers in 2016–2017. The high ratio of aging farmworkers who are unable to find alternative employment during the transition emerges as an essential impediment to increases in rice productivity, in addition to previously documented land-use-related issues. This demographic feature, along with government equity-targeting measures, hinders the farm amalgamation progress, further limiting efforts to enhance efficiency. Thus, the goals of economic efficiency and social equity do indeed appear to be contradictory features of Vietnam's rice policies, posing a significant development challenge for the country's current and likely future progress.

1. Introduction

Since 1986, Vietnam has become a model of economic development, in which price-guided market principles and open trade have blended within the framework of democratic centralism, driving rapid economic growth and impressive poverty reduction. However, inequality in Vietnam has been on the rise (World Bank, 2012), contrary to prevailing socialist principles. One of the main forces at play is that the benefits of integration with the world economy have accrued disproportionally to the non-agricultural sector, resulting in a widening rural–urban income gap (World Bank, 2018). At the same time, labor remains concentrated in agriculture, a sector that has been shrinking substantially in its contribution to GDP (Nguyen, Do, Kay, & Kompas, 2020; Tarp, 2017).

To address this income gap, Vietnamese policy has focused on agriculture, the countryside and peasantry (the so-called 'three nongs' issue) after joining the World Trade Organization (WTO) in 2007. Specifically, it has highlighted the role of 'three nongs' as *"the basis and an important force for socio-economic development and maintaining political stability"* (Resolution 26-NQ/TW). In this light, various policy measures, ranging from changes in land use, irrigation and technology to market and price reform, have been implemented to enhance efficiency, productivity and value-added in agricultural production, with a goal to eventually raise income for farmers. These measures are mainly aimed at the rice sector, which continues to play a vital political and socio-economic role in Vietnam (Nguyen et al., 2020).

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In this context, the objective of this paper is twofold. We examine (a) whether productivity and profitability increased in rice production over our study period and (b) investigate what factors would have hindered these changes. To do so, we first focus on regional profit, terms of trade (TT), total factor productivity (TFP), and components of technical efficiency during 2000–2016. We find a substantial fall in farmers' profit, which was largely driven by the fall in TT. This fall in TT happened amid and despite the government's efforts to reverse this outcome since labor costs, which accounted for about 50% of total costs, increased much faster than output prices, given the high economic growth of Vietnam. At the same time, there was a contraction in the production frontier and the progress in productivity across regions over the whole period was mixed. The result is likely related to the country's limited investment in research and development, land degradation caused by crop intensity, extensive chemical use, and climate change. But more importantly, the country's restrictions on land accumulation and the requirement of planting rice on rice-only designated land have limited the gains that could possibly be achieved in technical, scale, and mix efficiency in most regions.

We further identify impediments to technical efficiency by taking advantage of the 2004 and 2014 Vietnam Household Living Standards Survey (VHLSS) data and semi-structured interviews with farmers and various stakeholders in the rice sector in 2016–2017. The VHLSS data collected by the General Statistical Office (GSO) are the only nationally representative surveys that contain questions on land use at the plot level. Our regional stochastic frontier analysis shows that a high ratio of elderly farm members (55 years old or older) has emerged as an important impediment to rice productivity, in addition to previously documented land-related constraints and institutions. The latter factors also explain the technical inefficiency found in region-specific production frontiers and the efficiency gap between the regional frontiers and the meta-frontier (i.e., the envelope of all regional frontiers). Our interviews reveal a subsistence-production trap for most farmers, especially those who cannot find alternative employment due to their mature age and the lack of appropriate skills. The result suggests that rural Vietnam will be further left behind due to bearing a double-burden of an aging unskilled population and the smaller share in the gains from the country's export-led economic growth.

Our paper complements a related and now influential literature which tries to understand cross-country productivity differences in agriculture, such as Kuznets (1971) and Gollin, Lagakos, and Waugh (2014), among many others. Two main and recently-proposed theories include distortions that misallocate resources across farms (Adamopoulos & Restuccia, 2014) and self-selection of relatively unproductive workers to work in agriculture in developing countries due to subsistence food requirements (Lagakos & Waugh, 2013). Our work differs in that it provides a detailed analysis of agricultural productivity in a rapidly-transforming country and transitional economy. In this sense, we contribute to the growing literature shedding light on country-specific determinants and the development of agricultural productivity in transitional economies.[1] Indeed, this literature has provided useful insights and important evidence to support economic theories that explain observed cross-country differences in agricultural productivity. A common feature of this literature, which differs from ours, is that their analysis is typically done at either the aggregate or household level, but not both.

Our work most closely relates to several studies that analyze productivity in Vietnam's rice sector. Previous assessments at the aggregate level were conducted for the periods until 2006, capturing the trend in the early stage of the reforms (Nghiem & Coelli, 2002; Kompas, Che, Nguyen, & Nguyen, 2012). Other studies, at the household level, focus on investigating factors that lead to rice farm inefficiency during a specific year, using either their own farm survey data or VHLSS data sets in the early 2000s (e.g. Huynh & Yabe, 2011; Linh, 2012; Kompas et al., 2012). Despite being more recent, the work by Diep (2013), Pedroso et al. (2018) and Trong and Napasintuwong (2015), examine only one of the eight regions in Vietnam, and thus is not country-representative. The availability of new and high-quality regional data, along with established agricultural censuses, the unique plot-level data of 2004 and 2014 in the VHLSS, and the in-depth interviews with farmers, provides an excellent opportunity not only to update the knowledge gained through the previous studies but even more so to assess whether government measures since the late 2000s have been effective.

2. Background

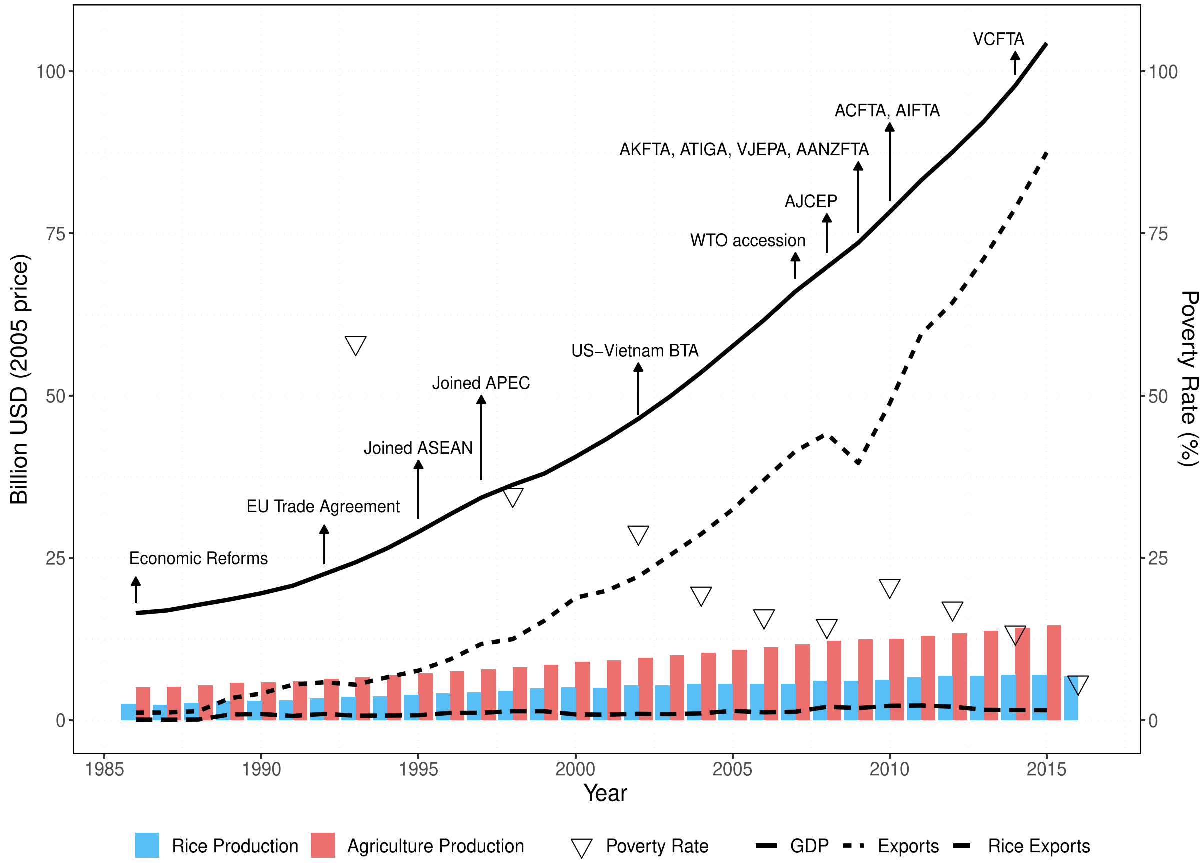
Vietnam has been one of the most successful stories in world economic development. Since the launch of economic reforms in 1986, the country has experienced high economic growth and moved from being one of the world's poorest nations into a lower-middle-income state. The pro-poor nature is arguably the most prominent feature of Vietnam's growth pattern, with the poverty rate falling by 51 percentage points during 1992–2017 when Gross Domestic Product (GDP) per capita increased by nearly fourfold over the same period (Fig. 1).

However, the driver behind this inclusive growth has changed over time. Earlier gains had been achieved thanks to the distribution of agricultural land to rural households and the incentives provided to them to increase their farm production (e.g. Che, Kompas, & Vousden, 2001; Nghiem & Coelli, 2002; Kompas et al., 2012). But these gains had been reaped by the early 2000s. Since then, the driving forces behind poverty reduction in Vietnam are job creation by the substantial expansion in trade due to the signing of dozens of multi- and bi-lateral trade agreements (Fig. 1), and the increased integration of agriculture to the market economy (World Bank, 2003, 2018).

The rapid export-led economic growth has shifted Vietnam's focus from poverty to inequality since the mid-2000s (VASS, 2011; World Bank, 2012, 2018). There are at least two reasons behind this shift. First, Vietnam is a socialist state in transition, and therefore, curbing inequality is vital for its political and social stability. Second, about 38 out of 50 million jobs in the economy are family farming, household businesses, or un-contracted labor (Cunningham & Pimhidzai, 2019). These jobs typically have low productivity, low profits, meager earnings, and little worker protection. Although administrative restrictions on migration, in the form of residence registration, have been considerably relaxed, thus allowing for considerable labor mobility across the country, other constraints such as age and a lack of human, physical, and financial capital remain substantial (Narciso, 2017). Hence, the poor are mostly rural dwellers and ethnic minorities who fail to benefit from the ongoing economic growth (World Bank, 2018; Nguyen, Kompas, Breusch, & Ward, 2017). This phenomenon goes hand in hand with the rapid expansion of the middle class in the urban areas, and hence the rural–urban gap has been widening (World Bank, 2018).

In this context, a new wave of agricultural reforms was initiated in 2007, with an aim to boost economic efficiency and social equity. For economic efficiency, Vietnamese policy has attempted to *"restructure the agricultural sector to enhance its value-added and sustainable development to increase farmers' income"* (Resolution 26-NQ/TW issued in 2007). To do so, two important measures

[1] For example, Gong (2018) discusses the case of China; Foster and Rosenzweig (2004) and Ghatak and Roy (2007) on India; Rahman and Salim (2013) on Bangladesh; Temoso, Hadley, and Villano (2018) on Botswana; and Anik, Rahman, and Sarker (2017) on South Asia.



Notes: GDP = Gross Domestic Product; VCFTA= Vietnam Chile Free Trade Agreement (FTA); ACFTA=Association of Southeast Asian Nations (ASEAN) China FTA; AIFTA = ASEAN India FTA; AKFTA = ASEAN Korea FTA; ATIGA = ASEAN Trade in Goods Agreement; VJEPA = Vietnam Japan Economic Partnership Agreement; AANZFTA = ASEAN Australia New Zealand FTA; WTO = World Trade Organization; EU = European Union;
Sources: Poverty rates are from VASS (2011); World Bank (2018) and other data are from FAO (2019).

Fig. 1. Pro-poor export-led growth in Vietnam (Notes: GDP = Gross Domestic Product; VCFTA = Vietnam Chile Free Trade Agreement (FTA); ACFTA = Association of Southeast Asian Nations (ASEAN) China FTA; AIFTA = ASEAN India FTA; AKFTA = ASEAN Korea FTA; ATIGA = ASEAN Trade in Goods Agreement; VJEPA = Vietnam Japan Economic Partnership Agreement; AANZFTA = ASEAN Australia New Zealand FTA; WTO = World Trade Organization; EU = European Union; Sources: Poverty rates are from VASS (2011), World Bank (2018) and other data are from FAO (2019).)

have been implemented. The first is the 2013 revised Land Law, which allows farmers to accumulate annual land, including rice land, from the previously-set limit of 6 hectares to now 30 hectares in the Mekong River delta, and from the limit of 4 hectares to now 20 hectares in other regions. As for perennial land, the limit has been increased from 20 hectares to now 100 hectares in the deltas and 50 hectares to 300 hectares in highlands/mountainous areas. In parallel, the land tax for allocated land was waved between 2003 and 2010, and reduced by half for accumulated land (2003 and 2010 (Revised) Land Law).[2] As the second measure, Vietnam reduced irrigation service fees in 2003 and then removed them in 2008 (Degrees No.115/ND-CP and No.143/ND-CP). This second measure has benefited rice farmers mostly since rice land represents about 80 percent of Vietnam's irrigated land. It is worth noting that the spending on irrigation has accounted for 60–80 percent of the total public expenditure on agriculture, on average, since the early 2000s. In comparison, research and development have represented less than three percent (MARD, 2013, 2017).

Regarding social equity, rice policies have become instrumental. The reason is that about 80 percent of rural households remained involved in rice production by 2014, while rice contributed about half of the calorie intake of rural dwellers (Nguyen et al., 2020; Ha, Nguyen, Kompas, Che, & Trinh, 2015). In this context, rice policies have substantial pro-poor implications.

At the risk of oversimplification, we classify equity-targeting policies into two groups. The first one seeks to achieve long-term food security by protecting an area of rice land that is sufficient to produce rice for the nation by 2030 (Decree 63/ND-CP in 2009, Resolution 17/2011/QH13 in 2011).[3] Accordingly, Vietnam is among the only two countries in the world in which farmers are not allowed to plant any crops other than rice in their rice-designated area (Markussen, Tarp, & Van den Broeck, 2011; Giesecke, Tran, Corong, & Jaffee, 2013). Given this crop constraint,

[2] Vietnam has been controlling farm size by setting limits on land allocation and accumulation. In particular, the former is the maximum amount of land granted by the state to a household; the latter is the maximum amount of land a household can accumulate via transactions on the land market.

[3] Chu, Nguyen, Kompas, Dang, and Bui, 2021 find that economic efficiency would be enhanced if 13% of the proposed protected cultivated rice land can be released into the pool of land for other crops. However, this release is pro-rich and thus implies a trade-off between economic efficiency and inequality in Vietnam.

the profit of rice production is the lowest among all annual crops (World Bank, 2018). To address this disparity, cash transfers of about \$20 per hectare of wet rice land and \$10 per hectare of dry rice land were provided to farmers during 2012–2015 (Decree 35/2015/ND-CP).

The second group of policies aims to ensure that rice farmers have at least a 30 percent profit (Document 430/TTg-KTN, 2010). To achieve this, the government has built big temporary storage depots to store paddy purchased from farmers during the harvest time when the price is low (Decision 1518/QD-TTg, 2009). Loans with subsidized interest rates were also provided to implement this purchase for the first few years, after the depots were built. Rice has been listed among 11 essential commodities which have been under price regulation by the government since 2012 (Price Law, 2012). This regulation can be implemented strictly due to the government's full control over rice exports and long-distance trade (Nguyen et al., 2020).

Against this background, we aim to assess to what extent there were profitability and productivity increases in rice production during the second wave of agricultural reforms, and investigate what may have prevented these or any increases in Vietnam.

3. Methods

We use both quantitative and qualitative methods to achieve our research aim. Specifically, our quantitative analysis is carried out at the regional and farm levels. We first measure and decompose regional productivity and profitability change using index numbers. We then identify factors that affect productivity using stochastic frontier analysis of farm data. Quantitative results are interpreted with the aid of semi-structured interviews with rice farmers. This section explains each of the methods.

3.1. The index number approach to measuring and decomposing productivity and profitability change

We follow O'Donnell (2010) to express profitability as the revenue-cost ratio:

$$PROF_{nt} \equiv \frac{P_{nt}Q_{nt}}{W_{nt}X_{nt}} \tag{1}$$

where Q_{nt} and X_{nt} are aggregate output and input quantities while P_{nt} and W_{nt} are aggregate output and input prices of decision making unit (DMU) n at time t.

This profitability can be decomposed into the product of TT and *multiplicatively complete*[4] TFP indices, and compared accross DMUs over time (O'Donnell, 2010) in the form:

$$PROF_{ms,nt} \equiv \frac{PROF_{nt}}{PROF_{ms}} \equiv \frac{P_{ms,nt}}{W_{ms,nt}}\frac{Q_{ms,nt}}{X_{ms,nt}} = TT_{ms,nt} \times TFP_{ms,nt} \tag{2}$$

where $P_{ms,nt} \equiv P_{nt}/P_{ms}$ is an output price index, $W_{ms,nt} \equiv W_{nt}/W_{ms}$ is an input price index, $W_{ms,nt} \equiv Q_{nt}/Q_{ms}$ is an output quantity index, $X_{ms,nt} \equiv X_{nt}/X_{ms}$ is an input quantity index, $TT_{ms,nt} \equiv P_{ms,nt}/W_{ms,nt}$ is a TT index measuring the growth in output prices relative to the growth in input prices, and $TFP_{ms,nt}$ is a *multiplicatively complete* TFP index comparing the TFP of DMU n in periof t with the TFP of DMU m in period s. It is worth noting that Eq. (2) implies that changes in TT can induce changes in TFP, at least in the case of DMUs who have access to a variable returns to scale (VRS) production technology and whose preferences are strictly increasing in net returns (O'Donnell, 2010).

[4] O'Donnell, 2010 formally defines the *multiplicatively complete* TFP index is the ratio of an aggregate output to an aggregate input and the aggregator functions must satisfy the monotonicity, homegeneity, identity, commersurability and proportionality axioms.

DMU performance in productivity or the so-called TFP *efficiency* (TFPE) can be measured by the ratio of obverved TFP to the maximum TFP possible using the available technology (TFP^*) (O'Donnell, 2012) in the form:

$$TPFE_t = \frac{TFP_t}{TFP_t^*} \tag{3}$$

Meanwhile, the Farrell (1957) measures of output-oriented technical efficiency (OTE) and input-oriented technical efficiency (ITE) can be defined in terms of aggregate outputs and inputs in the form:

$$OTE_t = \frac{Q_t}{\bar{Q}_t} = D_O^t(x_t, q_t) \leqslant 1 \quad \text{and} \quad ITE_t = \frac{\bar{X}_t}{X_t} = D_I^t(x_t, q_t)^{-1} \leqslant 1 \tag{4}$$

where $\overline{Q}_t$ is the maximum aggregate output that is technically feasible using input x_t to produce a scalar multiple of output q_t; Q_t is observed aggregate output; D_O^t is the output distance function representing the t-period technology; likewise, $\overline{X}_t$ is the minimum aggregate input possible when using a scalar multiple of input x_t to produce output q_t; X_t is observed aggregate input; D_I^t is the input distance function representing the t-period technology.

To this end, if the output and input distance functions are well-defined, and TFP^* in each period is finite and non-zero, then any *multiplicatively complete* TFP index can be exhaustively decomposed into measures of technical change and efficiency change, as shown by O'Donnell (2012). Specifically, the output-oriented decomposition is as follows:

$$\begin{aligned} TFP_{ms,nt} = \underbrace{\left(\frac{TFP_t^*}{TFP_s^*}\right)}_{\text{Technicalchange}} \underbrace{\left(\frac{TFPE_{nt}}{TFPE_{ms}}\right)}_{\text{Efficiencychange}} &= \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{nt}}{OTE_{ms}}\right)\left(\frac{OME_{nt}}{OME_{ms}}\right)\left(\frac{ROSE_{nt}}{ROSE_{ms}}\right) \\ &= \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{nt}}{OTE_{ms}}\right)\left(\frac{OSE_{nt}}{OSE_{ms}}\right)\left(\frac{RME_{nt}}{RME_{ms}}\right) \end{aligned} \tag{5}$$

and the corresponding input-oriented decomposition is as follows:

$$TFP_{ms,nt} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{nt}}{ITE_{ms}}\right)\left(\frac{IME_{nt}}{IME_{ms}}\right)\left(\frac{RISE_{nt}}{RISE_{ms}}\right) = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{nt}}{ITE_{ms}}\right)\left(\frac{ISE_{nt}}{ISE_{ms}}\right)\left(\frac{RME_{nt}}{RME_{ms}}\right)$$

where

$$\begin{cases} OME \text{ and } IME \text{ are pure output- and input-oriented mix efficiency} \\ OSE \text{ and } ISE \text{ are pure output- and input-oriented scale efficiency;} \\ ROSE \text{ and } RISE \text{ are output- and input-oriented residual scale efficiency; and} \\ RME \text{ is residual mix efficiency.} \end{cases}$$

Thus, the technical change in Eqs. (5) and (6) represents the movement of the production frontiers caused by any changes in the environment in which production takes place (O'Donnell, 2010). On the other hand, the efficiency change, which captures movements toward or away from the frontier, is associated with technical efficiency, scale efficiency, mix efficiency and residual mix efficiency.

Among many *multiplicatively complete* TFP indexes, we choose the Farë-Primont index for its satisfaction of the transitivity axiom, allowing for multilateral or multi-temporal comparison (O'Donnell, 2014).

3.2. The stochastic meta-frontier analysis of rice farm data

Vietnam is an elongated country, and therefore, rice farmers in different regions face different production opportunities. Under these circumstances, they make various feasible input–output combinations for their production. Thus, it is important to estimate region-specific production frontiers and measure the relative performance of farmers within each region and compare it across the country. To do so, we use the meta-frontier production function model, developed by Battese, Rao, and O'Donnell (2004) to frame our analysis.

There are two reasons why we choose Stochastic Frontier Analysis (SFA) to find constraints to farm productivity. First, we use household data, which likely contains noise. Unlike DEA, SFA allows consideration of both random variations in output for a given level of inputs and factors other than inputs that influence efficiency (Aigner, Lovell, & Schmidt, 1977; Meeusen & van Den Broeck, 1977). The main downside of SFA is its lack of flexibility in model structure. Therefore, the choice between DEA and SFA boils down to whether model flexibility or precision in noise separation is more important in each application. This leads to the second reason for our choice, namely, production theory in economics is relatively well-established to allow us to make some standard assumptions about the farm production function.

Admittedly, there would be concerns over the inherent endogeneity issue when using the SFA method to estimate output and input distance functions. This issue arises from the possibility that some determinants of production are only observed or predictable by farmers, not researchers, and farmers' input allocations are chosen by their optimizing behavior, where input choices may be correlated with these farmers' observed/predictable components (Marschak & Andrews, 1944; Shee & Stefanou, 2015). This issue, however, would likely be negligible in the context of Vietnam since the use of land, which is the key input in rice production, is determined by the government. Indeed, Vietnam is one of the only two countries in which farmers must plant rice in rice-designated land (Aung, Nguyen, & Sparrow, 2019; Chu et al., 2021). The country's 'overprotection' of rice land makes the farmland considered in our data mostly, if not all, rice-designated (Markussen, Tarp, & Van Den Broeck, 2011; Chu et al., 2021). This mandatory land use brings together other inputs required for rice production, making them all largely exogenous.

With this in mind, we follow the previous literature to specify the production function for farm i in the region k at the period t in the form:

$$Y_{it} = e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k - U_{it}^k} \equiv f\left(X_{it}, \beta^k\right) e^{V_{it}^k - U_{it}^k} \tag{7}$$

where Y_{it} and $\mathbf{x_{it}}$ respectively denote the scalar vector of (transformations of) output and inputs; β^k is a vector of production frontier parameters of kth region to be estimated. The composite error term has two components, namely the usual random noise $v_{it} \sim N(0, \sigma_v^{k2})$ and the non-negative random variable $u_{it} \sim N^+\left(z_{it}\delta^k, \sigma_u^{k2}\right)$, capturing farm-specific technical inefficiency in production in the form:

$$u_{it} = z_{it}\delta^k + w_{it} \tag{8}$$

where z_{it} is a vector of explanatory variables, δ^k is a vector of unknown coefficients and w_{it} is the random noise (Battese & Coelli, 1995).

If the production technology in all regions is the same, we can write the Eq. (7) for the whole country as follows:

$$Y_{it} = f(X_{it}, \beta) e^{V_{it} - U_{it}} \tag{9}$$

where β is a vector of production frontier parameters of the whole country to be estimated using the data pooled from all regions. But if the technology varies by region, then each region will have its own production frontier. Existing literature defines a frontier that envelops all regional frontiers as a meta-frontier:

$$Y_{it} = f\left(X_{it}, \beta^M\right) e^{V_{it}^M - U_{it}^M} \tag{10}$$

where β^M is a vector of production meta frontier parameters; other notations have the meanings similar to those of their counterparts in Eq. (7), but at the country level.

It is worth noting that β^M cannot be estimated using the pooled data with one SFA run as in Eq. (9). The frontier constructed that way is not guaranteed to envelop all regional frontiers (O'Donnell, Rao, & Battese, 2008). Therefore, there is a consensus on a two-step procedure, in which the first step is to use SFA to get region-specific frontiers by estimating Eq. (7). Existing literature remains divided, however, on the estimation method for the second step to construct a meta frontier. O'Donnell et al. (2008) and Kerstens, O'donnell, and Van de Woestyne (2019) suggest the use of DEA while Huang, Huang, and Liu (2014) propose SFA. We choose the latter method because we are concerned not only estimating the gap between the region-specific frontiers and their meta-frontier, but also on what could explain this gap, in addition to the statistical inference made possible only with SFA.

Specifically, noting that Eqs. (7) and (10) are equal, we have the following equation:

$$\underbrace{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k}}_{\text{Region-specific frontier}} = \underbrace{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}}_{\text{Meta frontier}} \underbrace{e^{-\left(U_{it}^M - U_{it}^k\right)}}_{\text{Technology gap ratio}} \tag{11}$$

The technical efficiency TE^k of a farm being benchmarked with the regional frontier is defined as:

$$TE_{it}^k = \frac{Y_{jit}}{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k}} \equiv \frac{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k - U_{it}^k}}{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k}} = e^{\left(-U_{it}^k\right)} \tag{12}$$

while the corresponding TE^M for the meta frontier is in the form:

$$TE_{it}^M = \frac{Y_{jit}}{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}} \equiv \frac{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M - U_{it}^M}}{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}} = e^{\left(-U_{it}^M\right)} \tag{13}$$

It is worth emphasizing that the definitions in Eqs. (12) and (13), proposed in the seminal work by Battese and Coelli (1988), have been used in multiple popular frontier textbooks and computation packages (e.g. Coelli, 1996; Coelli, Rao, O'Donnell, & Battese, 2005; Coelli, Henningsen, & Henningsen, 2020). It follows that the technology gap ratio between a region-specific frontier and the meta-frontier is:

$$TGR_{it} = \frac{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k}}{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}} = e^{-\left(U_{it}^M - U_{it}^k\right)} \tag{14}$$

which can be estimated directly from Eq. (11). We note that existing literature, including the work by Huang et al. (2014), excludes the noise in their formulas of TGR. However, this exclusion is at odds with the standard definition of frontier output (for example, see Coelli et al., 2005, p. 186).

To this end, the relationship between the farm performance relative to the region-specific and the meta frontiers can be shown as follows:

$$TE_{it}^M = \frac{Y_{jit}}{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}} \equiv \frac{e^{\mathbf{x}_{it}'\beta^k} e^{V_{it}^k}}{e^{\mathbf{x}_{it}'\beta^M} e^{V_{it}^M}} \times e^{-U_{it}^k} = TGR_{it} \times TE_{it}^k \tag{15}$$

In terms of estimation, parameters of both models (7) and (8) can be estimated simultaneously and consistently using the maximum likelihood (ML) estimator (Wang & Schmidt, 2002). The likelihood function is expressed in terms of the variance parameters, $\sigma^{k2} = \sigma_u^{k2} + \sigma_v^{k2}$ and $\gamma^k = \sigma_u^{k2}/\sigma^{k2}$ where $\gamma^k \in [0, 1]$. The SFA model specification is appropriate only when γ^k approaches 1. This specification can be tested using a likelihood ratio test which follows a mixed chi-square distribution (Coelli & Battese, 1996), while the test for the need of having region-specific frontiers can be done by comparing the likelihood of the Eq. (9) with the sum of the likelihoods of the Eq. (7) for all regions. If the test suggests the need for region-specific frontiers, then the parameters of the meta-frontier (Eq. (13)) can be estimated using a two-step SFA approach as follows:

$$\text{Step 1}: \quad Y_{it} = e^{\mathbf{x_{it}}'\beta^k} e^{V_{it}^k - U_{it}^k}$$
$$\rightarrow \quad \text{get} \quad e^{\mathbf{x_{it}}'\beta^k} e^{\widehat{V_{it}^k}} \quad \text{for each region } k \tag{16}$$

$$\text{Step 2}: \quad e^{\mathbf{x_{it}}'\hat{\beta}^k} e^{\widehat{V_{it}^k}}$$
$$= e^{\mathbf{x_{it}}'\beta^M} e^{V_{it}^M} e^{-\left(U_{it}^M - \widehat{U_{it}^k}\right)} \quad \text{for the whole country} \tag{17}$$

We note that our approach to estimation differs from Huang et al. (2014) in the aforementioned second step in that we keep model (estimated) *random* noise ($e^{\widehat{V_{it}^k}}$). Without this noise, the "error" in the second step in Huang et al. (2014) is purely the *estimation* error ($e^{\left(V_{it}^k - U_{it}^k\right) - \left(\widehat{V_{it}^k} - \widehat{U_{it}^k}\right)}$) of the first step (see Huang et al., 2014, p. 245). Our approach ensures that the ML estimates of β^M and their standard errors are consistent because it keeps the random noise required to correct OLS biased estimates in any SFA estimation (Coelli et al., 2005, pp. 188–189). Without this noise, the properties of ML estimates of β^M in Huang et al. (2014) are unknown.

Finally, we note that while the second step of our approach gives ML estimates of β^M, the *TE* estimated in this step is the *TGR*, not TE^M, and the impact of any exogenous variables *Z* should be interpreted as factors explaining the gap between the region-specific frontier and the meta-frontier.

3.3. Semi-structured interviews with rice farmers

To aid the interpretation of quantitative results, we use information from semi-structured interviews with rice farmers in three key rice-producing provinces. These interviews are part of a comprehensive qualitative study of the rice sector in Vietnam described in Nguyen et al. (2020). Each of them contains two parts. The first part has structured questions to get an overview of farmers' production, sales, revenues, and profit, and whether their products were sold for domestic consumption or exports. The second part has open questions, asking about their production plan, the support they have received from the Government, and the challenges they have faced.

4. Data and model specification

This section describes the data sources, variables, and model specification to implement our methods. All values are in 2010 constant prices, and adjusted for differences among regions using the regional price index (RCPI). Please see Appendix A for more information on RCPI.

4.1. Regional data for measuring and decomposing productivity and profitability change

Regional productivity and profitability change are measured and decomposed using input and output prices and quantities. The output is paddy, while the input includes land, labor, capital, and materials, which in turn consist of fertilizer, pesticides and seeds. As the data to construct output and input time series come from various sources, adjustment and imputation is sometimes needed when specific elements are not available. There are eight regions in Vietnam, namely the Red River Delta (RRD), the North East (NE), the North West (NW), the North Central Coast (NCC), the South Central Coast (SCC), the Central Highlands (CH), the South East (SE) and the Mekong River Delta (MRD). We combine data for MRD and SE, defined as SE&MRD, because SE does not have much rice production due to being the largest economic hub in Vietnam as well as having similar topographic conditions as MRD. See Appendix B for further details.

4.2. Household data for the stochastic frontier analysis and model specification

Stochastic frontier analysis is carried out using farm data from VHLSS in 2004 and 2014. As with other VHLSS, these two surveys are nationally representative and collected by Vietnam's General Statistical Office with technical support from the World Bank. However, being different from other VHLSS, they have an extended module on agriculture, which provides us with essential information to determine factors that restrict farm productivity. As our analysis focuses on rice production, following Kompas et al. (2012), we limit our sample to households whose rice revenues account for about three-quarters of total crop revenues. To this end, the pooled data set used for this paper has about 5900 farm-households in total.

We start with a general model, in the form of translog, to provide the local second-order approximation to any production frontier (Christensen, Jorgenson, & Lau, 1973). Furthermore, to accommodate technical change from 2004 to 2014, we follow Kumbhakar, Wang, and Horncastle (2015) adding a time dummy for the year 2014 ($d14$) and its interactions with all input variables. Hence the specification for a region's frontier production function is in the form:

$$\ln y = \underbrace{\beta_0 + \sum\nolimits_g \beta_g lnx_g + \frac{1}{2}\sum\nolimits_g \sum\nolimits_h \beta_{gh} lnx_g lnx_h}_{\text{Translog}}$$
$$+ \underbrace{\beta_t d14 + \sum\nolimits_g \beta_{gt} lnx_g d14}_{\text{Technical change}} + v - u \tag{18}$$

where $\beta_{gh} = \beta_{hg}$ and $u = \delta_0 + \sum_m \delta_m z_m + w$ (as described in Eq. (8)). Note that we suppress all the farm and time indexes in all variables in Eq. (7) to ease presentation.

Table 1 presents the summary statistics of variables for each region's production and technical inefficiency models in 2004 and 2014. Before discussing these results in detail, it is worth noting that some changes over time can be explained by the sampling variation since sample estimates using two different cross-sectional surveys, carried out at different points in time, are expected to be different. However, quite often, the changes likely stem from substantive changes in physical, social and economic environment in which rice production takes place.

We start with the model outcome which is the farm's annual rice output quantity. A quantity measure is used to avoid complications caused by intertemporal and spatial price effects (Aigner et al., 1977). On average, a farm produced about 2–3 tonnes of rice per year in 2014, reducing by 5–15 percent from a decade prior. The exception is SE&MRD, in which the corresponding number in 2014 was 17.5 tonnes, increasing by about 60 percent over ten years. This result is plausible as this region has the highest comparative advantage in rice production.

Our stochastic production frontier has six inputs, all of which matter to rice production. Land (*LAN*) is the total area of annual cropland, measured in hectares. Labor is split into two variables, namely household labor (*FLAB*), measured in hours, and hired labor (*HLAB*), measured in money – a unit of measurement applied to the remaining inputs. Capital (*CAP*) covers both rentals if farmers rent capital goods, primarily machines and equipment, for production, and depreciation if they own them. Finally, fertilizer (*FER*) and pesticide (*PES*) are the costs of these materials, respectively.

As seen in Table 1, all inputs have increased over time in all regions, except for household labor and land area. Indeed, household labor has reduced by about a quarter, being offset by hired labor. Meanwhile, farmland has increased by 20 percent, to 1.24 ha, in SE&MRD, the most favorable region for rice production,

Table 1
Farm rice summary statistics by region.

Variable	Unit	2004							2014						
		RRD (1)	NE (2)	NW (3)	NCC (4)	SCC (5)	CH (6)	SE&MRD (7)	RRD (8)	NE (9)	NW (10)	NCC (11)	SCC (12)	CH (13)	SE&MRD (14)
Model outcome variables															
Rice quantity	tonnes	2.31 (1.3)	2.01 (1.08)	1.92 (1.2)	2.34 (1.65)	2.38 (3.08)	3.81 (4.11)	10.79 (11.19)	2.22 (1.45)	1.7 (1.05)	1.79 (1.52)	2.13 (1.55)	2.39 (2.16)	3.23 (4.35)	17.56 (17.55)
Production Frontier variables															
Land area (LAN)	ha	0.24 (0.13)	0.38 (0.31)	0.99 (1.09)	0.34 (0.27)	0.37 (0.52)	1.01 (0.87)	1.08 (1.02)	0.25 (0.18)	0.38 (0.36)	0.82 (0.9)	0.37 (0.43)	0.35 (0.36)	0.8 (0.71)	1.24 (1.12)
Household labor (FLAB)	days	292 (195)	514 (291)	606 (373)	400 (230)	293 (184)	511 (298)	348 (227)	207 (121)	356 (208)	458 (237)	285 (207)	228 (161)	405 (230)	286 (173)
Hired labor (HLAB)	mil VND	0.17 (0.31)	0.09 (0.23)	0.08 (0.19)	0.17 (0.45)	0.44 (0.96)	0.4 (0.91)	2.59 (4.29)	0.51 (0.88)	0.23 (0.58)	0.21 (0.48)	0.39 (0.69)	0.5 (0.73)	0.53 (1.43)	2.9 (4.95)
Capital (CAP)	mil VND	0.74 (0.49)	0.5 (0.43)	0.45 (0.51)	0.73 (0.63)	0.72 (1.17)	1.07 (1.65)	3.62 (4.02)	1.48 (1.05)	0.89 (0.7)	0.81 (0.75)	1.33 (1.16)	1.46 (1.52)	1.38 (1.94)	9.03 (9.51)
Fertilizer (FER)	mil VND	1.54 (0.91)	1.38 (1.00)	0.66 (0.67)	1.58 (1.25)	1.5 (1.67)	2.04 (2.99)	5.95 (6.65)	1.85 (1.3)	1.41 (1.03)	1.03 (1.91)	1.71 (1.4)	2.06 (2.2)	2.05 (3.27)	12.88 (14.32)
Pesticide (PES)	mil VND	0.36 (0.3)	0.18 (0.17)	0.1 (0.19)	0.22 (0.25)	0.39 (0.38)	0.34 (0.51)	2.79 (3.72)	0.56 (0.54)	0.25 (0.26)	0.23 (0.54)	0.27 (0.29)	0.41 (0.49)	0.33 (0.51)	7.46 (10.72)
Technical Inefficiency Model variables															
Land fragmentation (FRA)	index [0,1]	0.65 (0.22)	0.64 (0.26)	0.63 (0.22)	0.62 (0.25)	0.53 (0.27)	0.45 (0.25)	0.21 (0.27)	0.46 (0.31)	0.55 (0.26)	0.49 (0.25)	0.44 (0.29)	0.48 (0.3)	0.36 (0.22)	0.18 (0.26)
Land in good conditions (TYP)	proportion	0.62 (0.38)	0.21 (0.35)	0.18 (0.31)	0.38 (0.4)	0.32 (0.42)	0.24 (0.4)	0.35 (0.47)	0.45 (0.48)	0.2 (0.38)	0.14 (0.32)	0.35 (0.46)	0.14 (0.32)	0.16 (0.36)	0.24 (0.42)
Land with land-use certificates (LUC)	proportion	0.67 (0.43)	0.82 (0.33)	0.65 (0.4)	0.71 (0.41)	0.81 (0.33)	0.36 (0.43)	0.9 (0.28)	0.5 (0.47)	0.78 (0.38)	0.56 (0.47)	0.58 (0.47)	0.78 (0.37)	0.4 (0.44)	0.82 (0.35)
Irrigated land (IRR)	proportion	0.98 (0.1)	0.84 (0.28)	0.54 (0.41)	0.85 (0.3)	0.79 (0.33)	0.56 (0.4)	0.94 (0.23)	0.95 (0.18)	0.69 (0.38)	0.52 (0.44)	0.78 (0.37)	0.74 (0.39)	0.46 (0.42)	0.87 (0.34)
Household head age (AGE)	years	47.9 (11.67)	44.22 (11.87)	40.92 (11.05)	45.79 (11.86)	48.36 (14.72)	46.12 (13.67)	46.96 (13.06)	52.43 (10.76)	45.77 (11.69)	41.76 (11.25)	49.96 (12.24)	49.96 (13.03)	42.93 (12.44)	49.67 (12.26)
Household head education (EDU)	years	8.38 (3.13)	7.38 (3.32)	5.5 (3.86)	8.61 (3.03)	6.08 (3.35)	4.28 (3.77)	5.55 (3.51)	8.83 (2.93)	7.04 (3.67)	5.36 (3.99)	8.51 (3.28)	7.04 (3.76)	4.78 (3.89)	5.94 (3.53)
Household male labor (MALE)	proportion	0.32 (0.33)	0.41 (0.26)	0.48 (0.23)	0.36 (0.29)	0.37 (0.35)	0.47 (0.27)	0.55 (0.32)	0.25 (0.35)	0.4 (0.32)	0.44 (0.26)	0.38 (0.36)	0.44 (0.4)	0.44 (0.3)	0.63 (0.35)
Household old labor (MAT)	proportion	0.22 (0.38)	0.14 (0.28)	0.06 (0.16)	0.16 (0.32)	0.29 (0.42)	0.13 (0.27)	0.15 (0.3)	0.39 (0.47)	0.16 (0.33)	0.08 (0.23)	0.28 (0.41)	0.42 (0.48)	0.17 (0.35)	0.28 (0.42)
Observations		944	741	274	533	306	118	684	485	622	223	338	173	76	404

Notes: Means and standard deviations are weighted using household weights in corresponding years. Monetary variables are measured in 2010 prices and adjusted for regional price differences. Statistics are calculated taking into account the underlying sampling design. Standard deviations are in brackets.

while reducing by a similar magnitude, to 0.8 ha, in NW and CH, the least favorable regions. It remains roughly the same in other areas: about 0.25 ha in RRD and 0.35–0.40 ha in others. These results suggest the persistent nature of subsistence rice production in Vietnam, even decades after the launch of economic reforms in 1986. In this context, rice production has been mechanized considerably, with expenses on capital nearly doubling between the two periods in all regions. The same is true with the use of pesticides in SE&MRD, RRD, and NW, which, unfortunately, has raised serious concerns over health and environmental damage in rural Vietnam (e.g. Toan, Sebesvari, Bläsing, Rosendahl, & Renaud, 2013; Lamers, Anyusheva, La, Nguyen, & Streck, 2011). Finally, fertilizer has also increased, especially in SE&MRD, and to a lesser extent, in RRD and NW.

The inefficiency model has eight explanatory variables, which can be classified into two groups. The first group relates to land, while the second one captures household demographics. For the land group, land quality is captured by two variables. One variable is the proportion of the land area, which has favorable conditions for rice production, to the total land area (*TYP*), while the other is the proportion of irrigated land to the total land area (*IRR*). Land ownership is measured by the ratio of the land area with land-use certificates to the total land area (*LUC*). Last but not least, land fragmentation (*FRA*) is quantified using the Simpson index, which takes into account both the number of plots and their sizes (Simpson, 1949), in the form:

$$FRA = 1 - \frac{\sum_{n=1}^{N} a_n^2}{\left(\sum_{n=1}^{N} a_n\right)^2} \tag{19}$$

where N is the number of plots, and a_n is the plot area n. *FRA*, by construction, is bounded by zero and one where zero indicates that a farm has only one plot or is not fragmented at all, while one implies that a farm has an infinite number of plots.

As seen in Table 1, land quality and ownership variables have worsened between the two periods. In particular, *IRR* fell by 10–20 percent in NW, CH, and SE&MRD, the regions that are affected the most by climate change. Meanwhile, *TYP* fell 20–50 percent in all regions, but NE and NCC, and *LUC* reduced by 20–25 percent in RRD, NCC, and SE&MRD. The reductions of quality paddy land (*TYP*) and land with land-use certifications (*LUC*) likely stemmed from rapid urbanization that has converted a large area of paddy land, much of which is in good condition and with land-use certificates, into other uses (e.g. Huu, Phuc, & Westen, 2015). The conversion is most visible in the main rice-producing regions, which are also economic hubs with high economic growth (e.g., RRD, SE&MRD, NCC, and SCC). In terms of land fragmentation, the evidence indicates some progress in addressing this issue in rural Vietnam.

The group of household demographics has four variables. The first two relate to the household head's age (*AGE*) and educational level (*EDU*). The last two are the proportion of household members who are male (*MALE*) and are 55 years or older (*MAT*), to the total number of household members involved in rice production. As seen in Table 1, the household head was older in 2014 in all regions, except for CH. There was little change in their education over time. Meanwhile, *MALE* changed considerably, especially in areas with high economic growth, reducing in RRD and increasing in SE&MRD and SCC. This change may well-reflect unemployment opportunities, which varied by region. For example, there are more textile factories in SE&MRD and SCC to attract disproportionately female labor, while the reverse is true in RRD, where there is more demand for men in construction sites. Finally, *MAT* has increased in all regions, but the most drastically, by 45–85 percent, in areas with or near economic hubs, namely RRD, SE&MRD, NCC, and SCC. This result is plausible since young and skilled rural labor can more easily move out of agriculture to find alternative employment, leaving only old and unskilled labor behind to do farm work (Phuong, Tam, Nguyet, & Oostendorp, 2008).

4.3. Semi-structured interviews

During December 2016–January 2017, 15 semi-structured interviews were carried out with farmers in three key rice-producing provinces. The provinces include Can Tho and An Giang in the Mekong River Delta and Nam Dinh in the Red River Delta. Farmers were selected from large-, medium- and small-sized groups to provide as diverse as possible perspectives.

5. Results

In this section, we first measure and decompose regional rice productivity and profitability, and then focus our attention on the factors that constrain technical efficiency at the household level. Semi-structured interviews provide additional insights. Computation, estimation and graphs are obtained using R, in particular Frontier (Coelli et al., 2020), Productivity (Dakpo, Desjeux, & Latruffe, 2018), and the ggplot2 (Wickham, 2011) packages in R. All R codes and data are available for replication.

5.1. Regional rice productivity and profitability change

Table 2 decomposes changes in profit in terms of TT and TFP. As the output price index has a 'structural break' at the year 2012 (Fig. 2), we split the period of our research interest into two sub-periods, or 2000–11 and 2012–16. As can be seen, farm profitability fell in all regions in both sub-periods, especially during 2012–16. The exceptions were NCC, CH, and SE&MRD in the first sub-period, over which farm profitability had increased by 10–37%.

Table 2 also reveals that farm profitability fell, largely due to steadily deteriorating TT and, to a lesser extent, TFP declining in the second sub-period. For the former, the TT index in rice production, alongside aggregate input, output, and labor input indexes since 2000 – the base year – are shown in Fig. 2. As can be seen, TT had been deteriorating at least since 2006 in all regions. Even the price spikes in 2008 and 2011 could only bring TT to the same level as the base year in SCC and SE&MRD. The underlying reason for this deterioration was twofold. The first was the steady increase in input prices, driven by rising labor costs. High economic growth and rapidly expanding non-agricultural sectors moved substantial amounts of rural labor out of agriculture and increased labor costs since the early 2000s. The second reason was the collapse in output prices since 2012. Under both circumstances, TT worsened over time.

Turning to TFP, across regions, improvement was seen in the first sub-period while a decline was recorded in the second sub-period. This result was largely driven by the expansion of the production frontier, TFP^*, in the first sub-period, followed by a contraction in the following period. Key factors driving this change include the country's limited investment in research and development, land degradation caused by excessive crop rotation and intensity, extensive chemical use, and climate change. At the same time, efficiency change, *TFPE*, was moderate and not uniform across regions. The changes in *TFPE* were also not clearly linked to any particular components of *TFPE*, but rather a combination of the changes in technical efficiency, pure output- and input-oriented scale efficiency, pure input-oriented mix efficiency and residual mix efficiency (which is not presented here for brevity). It is also worth noting that since there was only one output (rice) considered, there is no relevant change or gain in output-

Table 2
Changes in profit, terms of trade, total factor productivity, and efficiency using Farë-Primont Index.

Region	PROF = TT x TFP					TT					TFP = TFP* x TFPE					TFP*				
	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2
RRD	1.00	0.84	0.70	0.84	0.83	1.00	0.82	0.74	0.82	0.91	1.00	1.02	0.94	1.00	1.03	0.95	1.03	0.92	1.02	0.92
NE	0.98	0.94	0.70	0.96	0.75	1.26	1.11	0.89	0.88	0.80	0.78	0.85	0.79	1.00	1.03	0.95	1.03	0.92	1.09	0.94
NW	0.83	0.81	0.57	0.97	0.70	1.21	1.11	0.90	0.91	0.81	0.69	0.73	0.63	1.00	1.03	0.95	1.03	0.92	1.06	0.86
NCC	0.82	0.78	0.62	0.95	0.80	0.96	0.90	0.76	0.93	0.84	0.86	0.87	0.82	1.00	1.03	0.95	1.03	0.92	1.01	0.95
SCC	0.70	0.84	0.64	1.20	0.76	0.80	0.85	0.67	1.07	0.79	0.87	0.98	0.95	1.00	1.03	0.95	1.03	0.92	1.12	0.97
CH	0.65	0.71	0.51	1.10	0.72	0.92	0.86	0.66	0.94	0.76	0.70	0.83	0.78	1.00	1.03	0.95	1.03	0.92	1.17	0.94
SE&MRD	0.76	1.04	0.69	1.37	0.67	0.83	1.01	0.80	1.21	0.79	0.91	1.03	0.87	1.00	1.03	0.95	1.03	0.92	1.13	0.84

Region	TFPE					OTE					ITE				
	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2
RRD	1.00	0.99	0.98	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NE	0.78	0.82	0.83	1.05	1.01	0.86	0.89	0.90	1.03	1.02	0.88	0.89	0.90	1.02	1.01
NW	0.69	0.71	0.66	1.03	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NCC	0.86	0.84	0.86	0.98	1.03	0.94	0.91	0.95	0.96	1.05	0.94	0.91	0.95	0.97	1.04
SCC	0.87	0.95	1.00	1.09	1.05	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CH	0.70	0.80	0.81	1.13	1.02	0.97	1.00	1.00	1.03	1.00	0.98	1.00	1.00	1.02	1.00
SE&MRD	0.91	1.00	0.91	1.10	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Region	OME					OSE					IME					ISE				
	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2	00	11	16	Δ1	Δ2
RRD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NE	1.00	1.00	1.00	1.00	1.00	0.95	0.96	1.00	1.00	1.05	0.95	0.95	0.93	1.00	0.97	0.94	0.95	1.00	1.01	1.06
NW	1.00	1.00	1.00	1.00	1.00	0.92	0.79	0.71	0.86	0.89	1.00	1.00	1.00	1.00	1.00	0.92	0.79	0.71	0.86	0.89
NCC	1.00	1.00	1.00	1.00	1.00	0.99	0.97	1.00	0.98	1.03	0.94	0.94	0.92	1.00	0.97	0.99	0.96	1.00	0.97	1.04
SCC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.06	1.00	1.00	1.00	1.00	1.00	1.00
CH	1.00	1.00	1.00	1.00	1.00	0.80	0.83	0.87	1.03	1.05	0.94	0.96	0.98	1.03	1.02	0.79	0.83	0.87	1.04	1.05
SE&MRD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Δ1 and Δ2 are changes in the sub-periods 2000–2011 and 2011–2016. Base RRD 2000 = 1.

oriented mix efficiency. Overall, it is likely that the government's restrictions on land accumulation and the requirement of planting rice in rice-designated land limited the gains achieved in technical, scale, and mix efficiency in most regions, as typically seen in other countries when TT deteriorated (O'Donnell, 2010).

5.2. Stochastic frontier analysis

In this subsection, we first test and select model specification and then present estimation results.

5.2.1. Model specification tests

Table 3 presents likelihood ratio tests for model selection for each region. Specifically, the first three tests focus on the production model. We first test whether a translog model is favored against the null of having a Cobb-Douglas functional form. Put differently, does adding the third term in Eq. (18) sufficiently improve the likelihood ratio compared to the case without? The second and third tests check whether technical change is non-neutral. That is, whether TFP and returns to individual inputs statistically change over time? In essence, we test the fourth and fifth terms in Eq. (18). The remaining four tests focus on the inefficiency model. We test the nulls that technical inefficiency effects are absent in the fourth test, non-stochastic in the fifth test and follow a half-normal distribution in the sixth test. The seventh test inspects the null that all the explanatory variables in the inefficiency model are not statistically significant.

As can be seen in Table 3, we reject all null hypotheses at the 1% level in all regions, except for the third test, for which the null is rejected at 10% level in NW and CH and 25% level in NCC. We also reject the null that all regions share the same production technology (Likelihood ratio = 227.69; $X^2_{0.99}$ = 16.07). As a result, we choose the model specification as shown in Eq. (18) for each region and the meta-frontier.

5.2.2. Results of the production frontier models

Table 4 presents estimation results for region-specific frontier and meta-frontier models. It reveals a substantial fall in TFP, as seen in the negative sign for the time dummy coefficients, in most regions and in the meta-frontier. The fall is highly significant, corroborating and further elaborating on the aggregate trends discussed earlier. On the surface, this fall can be explained, in part, by the water shortage induced by climate change, which has accelerated in recent years, and the water conflicts with upstream countries that cause ongoing water pressure for rice production (Sebesvari, Le, Van Toan, Arnold, & Renaud, 2012; Chea, Grenouillet, & Lek, 2016; Nguyen, Kamoshita, Matsuda, & Kurokura, 2017). The frequency of natural hazards such as floods, droughts, and storms has also increased recently in Vietnam – one of the most climate-change vulnerable countries (MONRE, 2010; Hoang & Meyers, 2015). However, at a deeper level, there are more fundamental issues brought about by the government's social objectives in designing rice policies and the transition of the economy, which we will discuss in detail in the following subsection.

Table 4 also shows a uniform decrease in the return to land over time and across regions, as seen in their interactions with the time dummies. Lower returns to land are likely due to the reduction of fertile land, especially in the deltas. More specifically, the reduction is due to industrialization and economic growth [e.g.] (Huu et al., 2015), the depletion of soil nutrients due to long-lasting rice monoculture (Tran Ba, Le, Van Elsacker, & Cornelis, 2016; Tran Dung, van Halsema, Hellegers, Ludwig, & Wyatt, 2018), and the heavy reliance on chemical fertilizer in producing high-yielding varieties (HYV) – a factor that deteriorates soil fertility (Savci, 2012).

By contrast, the returns to other inputs over time varied by region. For example, household labor increased in importance in the South (i.e., SE&MRD and SCC), while it was hired labor in the North (i.e., SE&MRD and SCC). We note that hired labor in the

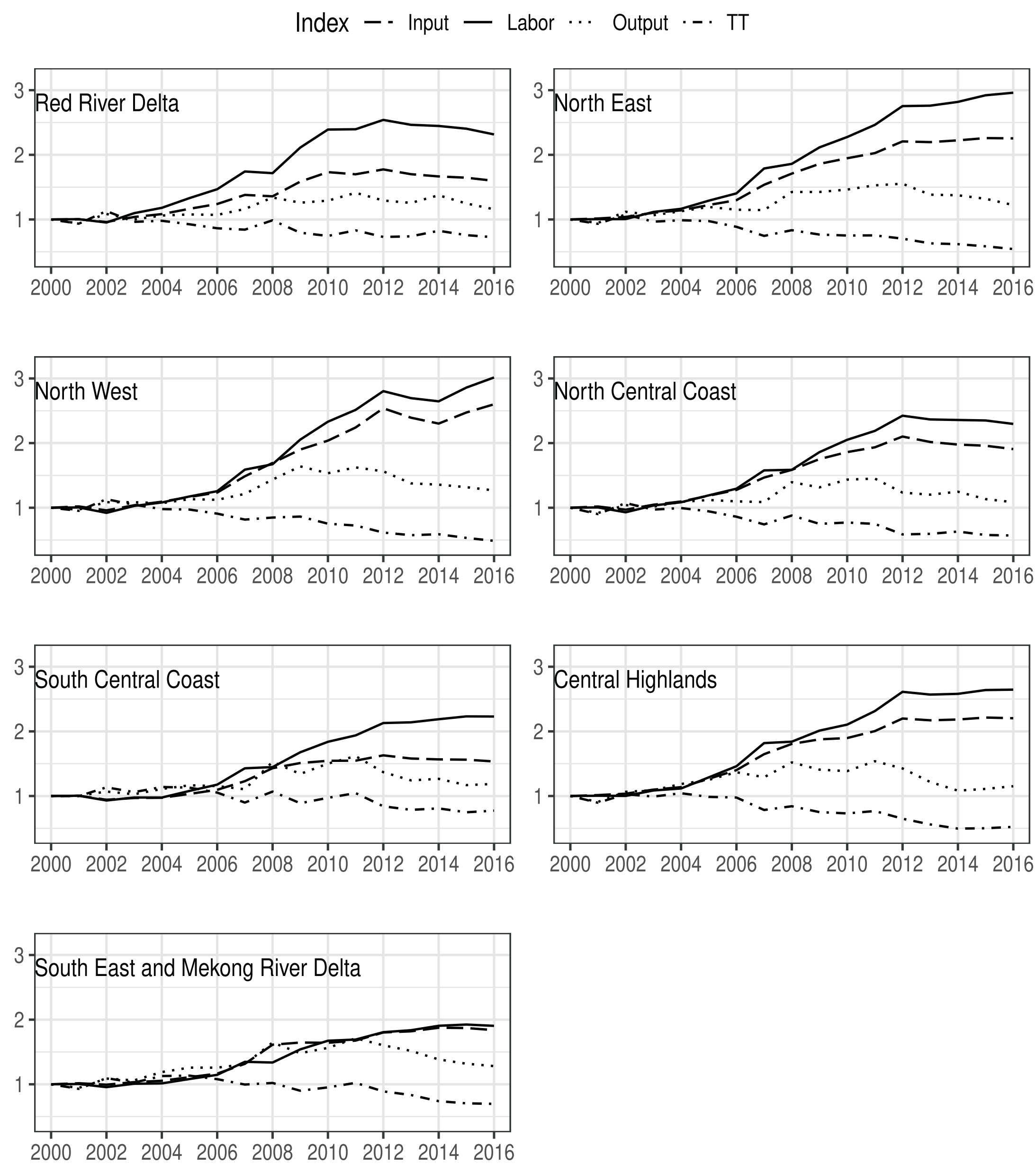


Fig. 2. Terms of trade, indices of input, output and labor prices in rice production.

Table 3
Specification test results by region.

Hypothesis	Likelihood ratio							$X^2_{0.99}$ value
	RRD	NE	NW	NCC	SCC	CH	SE&MRD	
1. H_0: CD production function	249.62	163.50	120.86	107.48	89.73	85.20	204.91	46.35
2. H_0: $\beta_t = \beta_{1t} = \beta_{2t} = \beta_{3t} = \beta_{4t} = \beta_{5t} = \beta_{6t} = 0$	180.47	131.83	24.56	123.05	45.24	15.79	41.44	17.76
3. H_0: $\beta_{1t} = \beta_{2t} = \beta_{3t} = \beta_{4t} = \beta_{5t} = \beta_{6t} = 0$	39.52	41.12	11.27	7.58	13.95	10.03	21.05	16.07
4. H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8$	112.20	129.25	67.66	187.41	89.77	47.70	123.05	22.53
5. H_0: $\gamma = \delta_0 = 0$	75.86	55.26	13.54	72.48	17.88	13.39	82.82	8.27
6. H_0: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0$	60.38	95.12	57.92	166.43	88.02	41.23	99.27	20.97
7. H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0$	46.95	77.21	53.73	158.64	84.86	38.66	75.87	19.38

Notes: The critical values are obtained from Kodde and Palm, 1986.

South was about 15-fold that in the North (Table 4), so this result may simply reflect the 'catching up' of the North with the inevitable trend of relying on the hired labor market in farm production as the economy grows. Meanwhile, higher returns to capital were

Table 4
Model results: dependent variable is rice quantity and prices are adjusted using RCPI.

	Stoch. Meta Frontier		RRD		NE		NW		NCC		SCC		CH		SE&MRD	
Production model coefficient and standard error (in brackets) estimates																
Constant	0.332**	(0.131)	0.505*	(0.285)	1.38**	(0.672)	−1.147	(1.47)	0.924*	(0.521)	0.154	(0.663)	2.586	(2.332)	−0.088	(0.378)
ln(x1) (Land)	−0.141***	(0.039)	−0.494***	(0.149)	0.086	(0.154)	−0.57**	(0.26)	−0.152	(0.176)	−0.717***	(0.255)	0.291	(0.395)	−0.442***	(0.134)
ln(x2) (Household labour)	0.323***	(0.041)	0.174**	(0.076)	−0.157	(0.206)	0.703	(0.466)	0.044	(0.162)	0.172	(0.193)	−0.604	(0.78)	0.305**	(0.131)
ln(x3) (Hired labour)	0.068**	(0.033)	−0.042	(0.074)	0.271	(0.169)	−0.443	(0.309)	−0.035	(0.128)	0.158	(0.158)	0.651	(0.439)	0.072	(0.097)
ln(x4) (Capital)	0.438***	(0.033)	0.284***	(0.077)	0.234**	(0.11)	0.843***	(0.245)	0.319**	(0.141)	0.666***	(0.208)	−0.127	(0.273)	0.514***	(0.121)
ln(x5) (Fertilizer)	0.45***	(0.04)	0.911***	(0.129)	0.542***	(0.178)	0.366	(0.23)	0.596***	(0.179)	0.823***	(0.269)	0.516	(0.372)	1.042***	(0.153)
ln(x6) (Pesticide)	0.068**	(0.027)	0.177**	(0.08)	−0.255**	(0.105)	0.209	(0.173)	0.239**	(0.113)	0.046	(0.229)	0.18	(0.362)	−0.161	(0.1)
ln(x1) ln(x1)	−0.106***	(0.008)	−0.573***	(0.051)	−0.162***	(0.032)	−0.018	(0.039)	−0.115***	(0.038)	−0.202***	(0.057)	−0.081	(0.078)	−0.242***	(0.039)
ln(x1) ln(x2)	0.071***	(0.006)	0.023	(0.02)	0.004	(0.022)	0.143***	(0.041)	0.067**	(0.026)	0.134***	(0.04)	0.013	(0.062)	0.101***	(0.022)
ln(x1) ln(x3)	0.038***	(0.005)	0.075***	(0.021)	0.039*	(0.02)	−0.026	(0.032)	0.087***	(0.026)	0.017	(0.034)	0.056	(0.062)	0.086***	(0.021)
ln(x1) ln(x4)	0.039***	(0.004)	0.056**	(0.024)	0.029*	(0.015)	0.053***	(0.02)	0.03	(0.025)	−0.029	(0.03)	−0.012	(0.04)	0.109***	(0.021)
ln(x1) ln(x5)	−0.068***	(0.005)	0.416***	(0.04)	−0.005	(0.021)	−0.091***	(0.022)	−0.036	(0.029)	0.057	(0.047)	−0.091*	(0.053)	−0.03	(0.029)
ln(x1) ln(x6)	0.004	(0.004)	0.025	(0.019)	−0.051***	(0.012)	0.015	(0.017)	0.004	(0.017)	0.027	(0.042)	0.063	(0.044)	0.042**	(0.02)
ln(x2) ln(x2)	−0.04***	(0.007)	−0.027**	(0.013)	0.039	(0.033)	−0.104	(0.075)	0.01	(0.027)	0.014	(0.031)	0.128	(0.13)	−0.007	(0.024)
ln(x2) ln(x3)	−0.003	(0.005)	0.026**	(0.011)	−0.032	(0.026)	0.05	(0.047)	0.014	(0.02)	−0.023	(0.025)	−0.079	(0.071)	0.02	(0.017)
ln(x2) ln(x4)	−0.033***	(0.005)	−0.01	(0.012)	−0.008	(0.017)	−0.108***	(0.037)	−0.01	(0.023)	−0.071**	(0.033)	0.057	(0.046)	−0.045**	(0.02)
ln(x2) ln(x5)	−0.03***	(0.006)	−0.009	(0.019)	−0.025	(0.026)	−0.009	(0.035)	−0.049*	(0.028)	−0.094**	(0.041)	−0.056	(0.063)	−0.141***	(0.026)
ln(x2) ln(x6)	−0.002	(0.004)	−0.008	(0.012)	0.028*	(0.016)	−0.028	(0.026)	−0.038**	(0.017)	0.022	(0.036)	−0.045	(0.057)	0.056***	(0.017)
ln(x3) ln(x3)	0.018**	(0.007)	−0.027	(0.018)	0.026	(0.033)	−0.223***	(0.08)	−0.016	(0.03)	0.059**	(0.028)	0.271**	(0.107)	0.003	(0.018)
ln(x3) ln(x4)	−0.024***	(0.005)	−0.024**	(0.012)	−0.026	(0.017)	0.035	(0.03)	0.023	(0.021)	−0.043	(0.028)	−0.058	(0.047)	−0.001	(0.017)
ln(x3) ln(x5)	0.008	(0.006)	−0.034	(0.022)	−0.033	(0.026)	0.014	(0.025)	−0.025	(0.025)	0.087**	(0.034)	−0.095	(0.06)	−0.034	(0.022)
ln(x3) ln(x6)	−0.005	(0.004)	0.005	(0.011)	0.03**	(0.015)	0.015	(0.021)	−0.035**	(0.017)	0.001	(0.033)	0.002	(0.05)	−0.04**	(0.016)
ln(x4) ln(x4)	0.063***	(0.004)	0.067***	(0.012)	0.059***	(0.015)	0.059**	(0.024)	0.071***	(0.021)	0.004	(0.03)	0.086**	(0.042)	0.094***	(0.02)
ln(x4) ln(x5)	−0.044***	(0.004)	−0.132***	(0.021)	−0.009	(0.016)	−0.061***	(0.021)	−0.092***	(0.024)	−0.027	(0.036)	−0.03	(0.037)	−0.077***	(0.02)
ln(x4) ln(x6)	0.00	(0.003)	−0.017	(0.011)	−0.012	(0.01)	−0.013	(0.012)	0.001	(0.013)	0.121***	(0.028)	0.016	(0.031)	−0.092***	(0.016)
ln(x5) ln(x5)	0.124***	(0.006)	−0.127***	(0.034)	0.067**	(0.027)	0.17***	(0.029)	0.195***	(0.038)	0.085	(0.052)	0.256***	(0.057)	0.103***	(0.039)
ln(x5) ln(x6)	0.017***	(0.003)	−0.037**	(0.018)	0.048***	(0.011)	0.005	(0.015)	0.033**	(0.016)	−0.089**	(0.035)	0.02	(0.035)	0.016	(0.021)
ln(x6) ln(x6)	−0.005	(0.004)	0.024*	(0.013)	−0.042***	(0.012)	0.021	(0.023)	−0.022	(0.018)	−0.074	(0.055)	−0.105*	(0.055)	0.07***	(0.02)
d2014 (Time dummy)	−0.362***	(0.051)	−0.601***	(0.119)	−0.136	(0.211)	−0.578	(0.431)	−0.422**	(0.185)	−0.787***	(0.267)	0.511	(0.64)	−0.633***	(0.172)
ln(x1) d2014	−0.039***	(0.008)	−0.199***	(0.035)	−0.08***	(0.028)	−0.006	(0.045)	−0.049	(0.037)	0.046	(0.054)	−0.145*	(0.079)	−0.074*	(0.04)
ln(x2) d2014	0.019**	(0.008)	0.024	(0.019)	−0.031	(0.032)	0.085	(0.068)	0.019	(0.03)	0.094**	(0.043)	−0.117	(0.106)	0.084***	(0.03)
ln(x3) d2014	0.01	(0.008)	0.05**	(0.02)	0.096***	(0.033)	−0.064	(0.059)	0.047	(0.031)	−0.009	(0.045)	−0.135	(0.098)	−0.025	(0.026)
ln(x4) d2014	−0.013**	(0.007)	0.047**	(0.02)	−0.081***	(0.02)	0.075*	(0.041)	0.017	(0.027)	−0.017	(0.043)	−0.011	(0.051)	0.072**	(0.031)
ln(x5) d2014	0.002	(0.008)	0.067**	(0.033)	0.061*	(0.032)	−0.02	(0.038)	−0.006	(0.037)	0.048	(0.056)	0.102	(0.07)	−0.029	(0.044)
ln(x6) d2014	0.011**	(0.006)	0.029	(0.018)	0.015	(0.018)	0.034	(0.031)	−0.027	(0.024)	−0.129***	(0.049)	0.102	(0.068)	0.037	(0.025)
Inefficiency model coefficient and standard error (in brackets) estimates																
Constant	0.126***	(0.026)	−0.615	(0.519)	0.75***	(0.258)	0.825***	(0.217)	0.589***	(0.134)	0.547***	(0.179)	2.011**	(0.785)	−1.953	(2.311)
Land fragmentation (FRA)	0.073***	(0.011)	0.377**	(0.186)	−0.155	(0.18)	0.083	(0.17)	0.351***	(0.12)	0.409**	(0.164)	−0.04	(0.386)	3.067	(3.04)
Land in good conditions (TYP)	−0.013	(0.008)	−0.319**	(0.151)	−0.216	(0.143)	−0.137	(0.152)	−0.384***	(0.109)	−0.248*	(0.143)	−0.725	(0.463)	−4.504	(4.805)
Land with certificate (LUC)	−0.007	(0.007)	0.355**	(0.173)	−0.17	(0.108)	−0.04	(0.103)	−0.131**	(0.058)	−0.068	(0.09)	−0.417	(0.316)	−2.921	(2.695)
Irrigated land (IRR)	−0.047***	(0.009)	−0.651**	(0.3)	−1.326*	(0.801)	−0.706**	(0.277)	−0.782***	(0.152)	−0.895***	(0.246)	−1.608*	(0.937)	−2.603	(2.394)
Male labourers (MALE)	−0.019**	(0.008)	−0.026	(0.053)	−0.131	(0.133)	−0.084	(0.187)	0.152*	(0.079)	−0.088	(0.095)	−0.607	(0.467)	−2.026	(2.022)
Age (AGE)	0.00	(0.00)	0.005*	(0.003)	−0.012	(0.01)	−0.008*	(0.004)	0.00	(0.002)	−0.002	(0.003)	−0.023	(0.016)	0.007	(0.016)
Education (EDU)	0.001	(0.001)	−0.007	(0.009)	−0.055	(0.039)	−0.005	(0.011)	−0.025***	(0.009)	−0.016	(0.011)	−0.092	(0.062)	−0.255	(0.222)
Mature labourers (MAT)	0.011	(0.008)	−0.038	(0.055)	0.45	(0.344)	−0.304	(0.412)	0.169**	(0.076)	0.161	(0.105)	0.836	(0.536)	0.561	(0.588)
Sigma squared	0.035***	(0.001)	0.193**	(0.081)	0.412*	(0.235)	0.168***	(0.042)	0.156***	(0.029)	0.153***	(0.038)	0.362**	(0.182)	1.672	(1.63)
Gamma	0.003	(0.053)	0.912***	(0.036)	0.88***	(0.063)	0.679***	(0.102)	0.835***	(0.036)	0.772***	(0.069)	0.844***	(0.086)	0.981***	(0.019)
Regional mean efficiency			0.86		0.82		0.74		0.79		0.8		0.75		0.85	
Technology gap ratio			0.89		0.88		0.87		0.88		0.89		0.88		0.92	
Meta mean efficiency			0.76		0.72		0.64		0.7		0.71		0.66		0.78	
Observations	5921		1429		1363		497		871		479		194		1088	

Notes: * p<0.1; ** p<0.05; *** p<0.01.

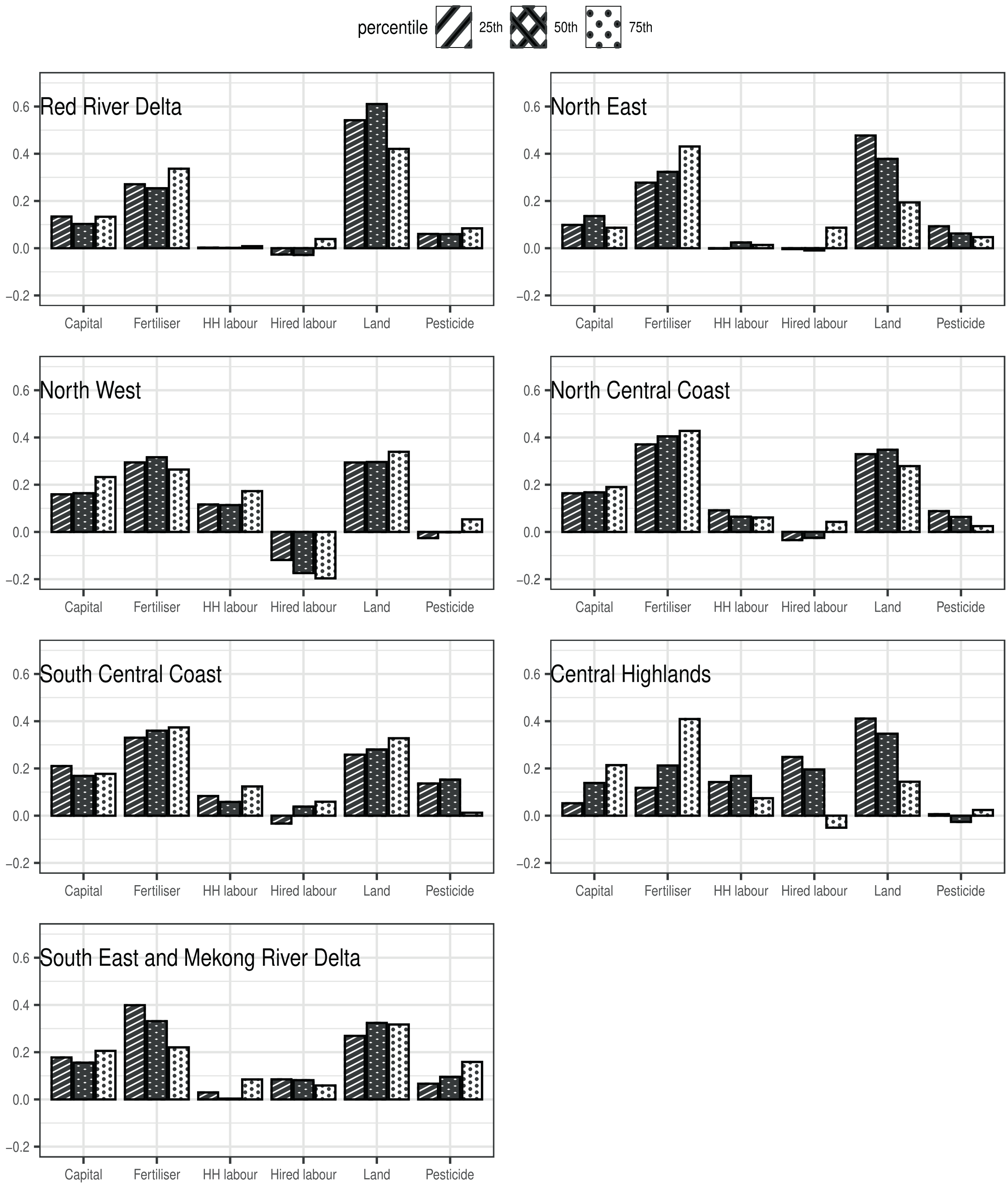


Fig. 3. Elasticities of rice with respect to inputs at the different percentiles of their use.

observed in the two delta regions, namely SE&MRD and RRD, and NW, but not across the country, indicating the lack of machinization necessary for large-scale and efficient production. Finally, labor-saving pesticides and fertilizer became increasingly important in some regions, consistent with factor substitution induced by rising real wage rates. Our findings on pesticide and hired labor are in line with the recent literature (e.g. Liu, Barrett, Pham, & Violette, 2020).

We further analyze elasticities of the output with respect to inputs. The coefficients of most inputs are statistically significant for the model outcomes, except for CH, which has a relatively small sample. Since the translog functional form implies non-linearity in elasticities, it is essential to estimate them at a specific point of the distribution such as the 25th, 50th and 75th percentile. Results are presented in Fig. 3.

Rice output responded the most to land and fertilizer, followed by capital as shown in Fig. 3. The impact of land was highest in RRD, and almost double those in SE&MRD at the 25th and 50th percentiles. However, there was no sign of economies of scale in land use. If anything, small farms seemed to use land more efficiently than the large ones, which is not unexpected given the low level of mechanization in Vietnam. Meanwhile, fertilizer had the most significant impact, being the most crucial input in NCC, but at a magnitude that was just marginally higher than those in other areas. Contrary to land, larger farms seemed to use fertilizer slightly more efficiently than smaller farms in most regions. However, the impact of capital was quite similar across regions and percentiles. This result underscores the limited changes from the impact or lack of mechanization on output when production scale increases.

The impacts of other inputs varied by region, largely driven by the cost of labor and off-farm employment opportunities available locally. For example, the impact of household labor was highest in the two poorest and mountainous regions, NW and CH, but lowest in regions with high economic growth, namely RRD, SE&MRD and NE. The impact of hired labor was the most significant in SE&MRD and CH, which export most of Vietnam's rice and perennial products, respectively. Finally, the impact of labor-substituting cheap pesticide was much higher in regions with high economic growth than those in the poorest ones. This result implies that in areas where competiton for labor was fierce, cheaper and more readily available chemicals were used more to substitute for increasingly expensive labor.

5.2.3. Results of the inefficiency model

Table 4 presents results of the inefficiency model. The mean of region-specific technical efficiency ranges from 0.74 to 0.85, of which the main rice-producing regions RRD and SE&MRD ranked the highest. There is not much variation in TGR, which ranges from 0.87 to 0.92. As expected, the frontiers of RRD and SE&MRD were the highest. Most coefficients are statistically significant in RRD, NCC, and SCC. The lack of statistical significance in other regions is likely due to little variance in the explanatory variables and/or small sample sizes.

Before discussing in results in more detail, it is worth noting that the negative coefficient of a variable in the inefficiency model means that efficiency will be improved when the variable increases and vice versa. Furthermore, variables of the meta-frontier model explain the gap between region-specific frontiers and the meta-frontier.

We first discuss the results for regional models. All variables helped increase productivity, except for the land fragmentation index (FRA) and the ratio of older household labor (MAT). Among the productivity-enhancing variables, the proportion of irrigated land (IRR) had the most impact. The result makes sense in the context of Vietnam's prevalent use of HYV, which relies primarily on irrigation and fertilizer. Likewise, as expected, a higher share of land classified as having favorable conditions for agricultural production (TYP) resulted in better rice quantity. Similarly, households with a bigger fraction of land area being granted land-use certificates (LUC) were more efficient since they were able to use LUC as collateral for loans and had stronger incentives to invest in their officially owned farms. The only exception was in RRD, where higher LUC was associated with lower efficiency. This result might be an artifact of urbanization where farms with higher LUC were more likely located in peri-urban areas and, therefore, would focus more on pursuing other off-farm job opportunities rather than producing rice, a low-return crop (Giesecke et al., 2013).

In the same vein, most of the demographic attributes also contributed to increasing efficiency. Among these variables, having a higher proportion of male labor (MALE) generated the largest impact. The result reflects not only the suitability of men in rice production but also the premium of being a man in the male-dominant culture of rural Vietnam. Having additional years of education (EDU) helped farmers to raise their production outcomes, but only in NCC. Finally, age (AGE) had some mixed but small impact on efficiency in RRD and NW.

Importantly, the results show that the higher land fragmentation (FRA), the lower was farm efficiency. Put differently, larger and less fragmented farms are more efficient. A similar finding is reported recently by Pedroso et al. (2018). So, in summary, there is strong evidence that land fragmentation remained a factor that severely hampered efficiency in rice production, even though more than ten years have elapsed since this impediment was first documented in the empirical literature (e.g. Pham, MacAulay, & Marsh, 2007; Kompas et al., 2012). While the evidence highlights the importance of land accumulation to farm production efficiency, it also underscores the slow progress in land consolidation in Vietnam, especially over the last decade. The government's support to rice farmers has likely hindered land amalgamation by making it cheap, if not free, to keep land idle or maintain subsistence production. This impact is further amplified by the tendency of holding on to land in order to pass it on to children as an inheritance, particularly in the North of Vietnam (Pham et al., 2007). To this end, the resulting widespread and persistent production of rice at subsistence scale has led to little change or regression in both productivity and efficiency observed across most of the regions, as discussed earlier.

We also observe an emerging factor that curbed productivity in rural Vietnam, namely the impact of able-bodied farmers who left agriculture to find off-farm jobs. Specifically, the higher the ratio of labor being 55 years old or older (*MAT*),[5] the less efficient was the farm in most regions and especially so (and statistically significant) in NCC, where out-migration was the highest (Nguyen, Raabe, & Grote, 2015). The result is plausible since elderly people had few options to move out of agriculture due to their mature age and a lack of skills suitable for more modern jobs. Furthermore, they might have been expected to stay home to take care of their grandchildren and conduct cultural practices. The semi-structured interviews with farmers in key rice-producing provinces reveal that two-thirds of them would maintain the same (subsistence) rice production for food security and employment for elderly people alone (Nguyen et al., 2020). Meanwhile, household data show that the MAT ratio was higher and had increased in the main delta regions and economic hubs (RRD, MRD, SCC, and SE), where young and skilled labor was much dearer, and it was easier to migrate (see Table 1). This phenomenon reflects a feature of a transitional economy, often referred to as 'greying' agriculture in the literature (e.g. Ye, 2015). As the economy continues to grow rapidly, and the government plans to use rice policy for social equity and food security purposes, alongside relaxing constraints to labor mobility, the issue of 'left-behind' elderly will continue to rein for many years to come. Hence, lower productivity is expected due to more extended land use, less multiple cropping, and land abandonment. Land accumulation and capital investment would thus be slow, while the application of new technology and the leverage of economies of scale would be obstructed.

Finally, the gap between the region-specific frontiers and the meta-frontier was attributed mainly to similar factors that explained the region's technical inefficiency. The result once again underscores the impediment of land fragmentation and the importance of good land, irrigation, and able-bodied farmers to enhancing efficiency in rice production.

6. Conclusion

Increasing productivity in agriculture is often deemed necessary to enhance rural income and ultimately narrow the urban–rural income disparity in transitional economies. This paper investigates the case of Vietnam during the high economic growth period (2000–2016), in which the country introduced policies to increase efficiency in rice production and income for rice farmers.

[5] We follow GSO (2018) in defining the group of mature labor at the age of 55 or older as distinct from other labor groups.

6.1. Findings and policy implications

We find a steadily decreasing trend in the TT for rice, indicating regression in farm income. Meanwhile, the productivity index has been falling in most regions due to the decline in technical change, along with little improvement in technical efficiency. The underlying reasons for these results are the high ratio of left-behind elderly farmers, in addition to previously-documented land-related issues such as land fragmentation and delay in the issuance of land-use certificates. We document, for the first time, evidence of Vietnam's 'greying agriculture', confirming a seemingly inevitable trend as the economy develops – an experience also observed in other more developed countries such as European countries, Japan and China.

The rise in the urban–rural gap is to be expected when the industry and services sectors grow faster than agriculture. Vietnam is not an exception in this regard. To curb this trend, the country has followed the lead of many more developed countries to move from taxing to subsidizing agriculture (Anderson, Rausser, & Swinnen, 2013). In the absence of an adequate social safety net, rice policy has become an ad hoc equity-targeting tool for the government. This approach, however, likely hinders land accumulation and limits enhanced productivity. Thus the goals of achieving economic efficiency and social equity appear contradictory to each other in Vietnam's rice policies, posing a significant development challenge for the country's current and likely future development.

6.2. Contribution, limitations and future research

This paper contributes to the now influential literature that tries to explain cross-country productivity differences in agriculture by providing detailed insights from Vietnam. This case is particularly interesting since Vietnam is a remarkably successful transitional economy with high economic growth, moderate (albeit increasing) inequality, and outstanding achievement in meeting development goals. The combination of detailed time-series and plot-level farm data, alongside interviews with farmers, makes this paper distinct from the existing literature. From this perspective, and although this paper presents the experience of Vietnam at a particular period in time, it is hoped that general lessons can be drawn and applied to similar development contexts.

Nevertheless, additional and better quality data would certainly enhance the analysis. Factors such as access to credit, extension services, and the market itself can affect farm inefficiency. Although having this information may not necessarily affect the quality of our model estimates, given region-specific and meta frontier models have been estimated, it would no doubt enrich the policy implications, and thus be worth considering in future research.

CRediT authorship contribution statement

Hoa-Thi-Minh Nguyen: Conceptualization, Methodology, Data curation, Software, Visualization, Formal analysis, Writing - original draft, Writing - review & editing. **Huong Do:** Conceptualization, Methodology, Data curation, Software, Visualization, Writing - original draft. **Tom Kompas:** Conceptualization, Methodology, Formal analysis, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix A. Spatial deflators

Vietnam is an elongated state, and the market is not fully integrated even for a staple like rice (Baulch, Hansen, Trung, & Tam, 2008). Thus, it is vital to consider spatial differences in prices or spatial deflators fully.

There exist two spatial deflators: the Regional Consumer Price index (RCPI) and the Spatial Cost of Living index (SCOLI), both provided by GSO. The former is calculated based on CPI data and disaggregated by region and urban/rural. It is constructed as an overall price index, and separate ones for food and non-food (Bales, 2001). This feature makes RCPI for food particularly suitable for this study which concerns rice, a main staple in the Vietnamese diet. RCPI is available for all rounds of biennial VHLSS from 2002 to 2016.

The second deflator is SCOLI, which has been proposed recently as a replacement for RCPI by Gibson (2009). He argues that the changes in data collection to estimate CPI from 2002 make RCPI less relevant to represent regional differences in prices. That is, data for CPI calculation were collected using a price survey which is separated from VHLSS since 2002; meanwhile, SCOLI used to be collected from a community market survey as part of the Viet Nam Living Standards Surveys (VLSS) in the 1990s. Since 2010, SCOLI has been consistently constructed based on the price data collected from a sub-sample of VHLSS locations. It is therefore deemed to better reflect the spatial differences in prices among regions and provinces. The downside of SCOLI, however, is that it is not available separately for food and non-food, and for the year 2004. Therefore, in this paper, we use RCPI.

Appendix B. Data compilation and adjustment for measuring and decomposing productivity and profitability change

Measuring and decomposing productivity and profitability change requires data on quantities and prices of output and inputs at the regional level. Vietnam has 63 provinces, which are normally grouped into eight regions in Vietnam, as follows:

1. RRD (Red River Delta): Ha Noi (including old Ha Tay), Vinh Phuc, Bac Ninh, Hai Duong, Hai Phong, Hung Yen, Thai Binh, Ha Nam, Nam Dinh, Ninh Binh
2. NE (North East): Quang Ninh, Ha Giang, Cao Bang, Bac Kan, Tuyen Quang, Lao Cai, Yen Bai, Thai Nguyen, Lang Son, Bac Giang, Phu Tho
3. NW (North West): Dien Bien, Lai Chau, Son La, Hoa Binh
4. NCC (North Central Coast): Thanh Hoa, Nghe An, Ha Tinh, Quang Binh, Quang Tri, Thua Thien Hue
5. SCC (South Central Coast): Da Nang, Quang Nam, Quang Ngai, Binh Dinh, Phu Yen, Khanh Hoa
6. CH (Central Highlands): Kon Tum, Gia Lai, Dak Lak, Dak Nong, Lam Dong
7. SE (South East): Ninh Thuan, Binh Thuan, Binh Phuoc, Tay Ninh, Binh Duong, Dong Nai, Ba Ria - Vung Tau, Ho Chi Minh
8. MRD (Mekong River Delta): Long An, Tien Giang, Ben Tre, Tra Vinh, Vinh Long, Dong Thap, An Giang, Kien Giang, Can Tho, Hau Giang, Soc Trang, Bac Lieu, Ca Mau

We combine data for MRD and SE. The reason is that SE does not have a lot of rice production due to being the largest economic hub in Vietnam and it has similar topographic conditions as MRD.

B.1. Data on quantities

Data on output and land quantities are readily available in the statistical yearbooks published by GSO (e.g. General Statistic Office, 2013). The data are reported at the provincial level. We aggregate them by region.

Labor quantity is the product of labor man-day per planted hectare and planted area. Unfortunately, we only have information on the labor man-day per planted hectare for one year, 2006, using the rural, agricultural, and fishery census of Viet Nam (Agrocensus) in 2006 (GSO, 2007). Thus we need estimates for other years. To do so, we adjust the information for 2006 using the relative change of labor quantity in agriculture reported by the Ministry of Agriculture and Rural Development (MARD) (MARD, 2011, 2017).

Physical capital is the combined capacity of tractors and buffalo-equivalent power. The number of tractors and their capacity in horsepower (hp) are available from Agrocensus in 2001, 2006, 2011, and 2016 (GSO, 2002, 2007, 2012, 2017). The numbers of ploughing cattle and buffalo are reported in annual statistical yearbooks by GSO and annual reports by the Department of Livestock Production under MARD (MARD, 2018). A cattle/buffalo, having an average weight of 250 kilograms, is considered equivalent to one hp (Kompas, Nguyen, & Van, 2011; Kompas et al., 2012). Temporal changes in the physical capital are made with the aid of the statistics supplied by the Department of Agroforestry Processing and Salt Industry under MARD (MARD, 2018).

Material inputs consist of chemical fertilizer, pesticide, and seeds. Quantities of each component in the materials are products of their corresponding amounts per planted hectare and the total planted area. The amount of fertilizer per planted hectare is calculated using the data of the Vietnam Living Standard Surveys (VLSS 1993 and 1998) and VHLSS (carried out biennially since 2002). The amount of pesticide per planted hectare is from Kompas et al. (2012), being 5.8 kg and 7.6 kg in the North and South until 2006. Since 2007, we increase this amount by 50 percent based on the information from the field survey in MRD of Viet Nam by Bordey, Moya, Beltran, and DC (2016) in 2011. The amount of seeds per planted hectare is from Agrocensus in 2006 (GSO, 2007) and updated for other periods using the survey data in An Giang and Dong Thap (An Giang DARD, 2012–2014; Dong Thap DARD, 2009–2014; Nguyen, Vo, & Huynh, 2015; Bordey et al., 2016).

B.2. Data on prices

Output prices are the farm gate prices of paddy collected monthly by Department of Trade and Prices, GSO, in 36 provinces during 2000–2016. These provinces include Ha Noi (including old Ha Tay), Hai Duong, Hai Phong, Thai Binh, Ha Nam, Ninh Binh, Cao Bang, Yen Bai, Thai Nguyen, Phu Tho, Son La, Hoa Binh, Thanh Hoa, Nghe An, Ha Tinh, Quang Tri, Thua Thien Hue, Quang Nam, Binh Dinh, Phu Yen, Khanh Hoa, Dac Lak, Lam Dong, Ninh Thuan, Binh Thuan, Binh Phuoc, Dong Nai, Long An, Tien Giang, Ben Tre, Vinh Long, Dong Thap, An Giang, Kien Giang, Can Tho, Bac Lieu.

Calculating land prices for planted land is challenging since the regional data on planted land have no information on land quality, based on which the land tax is levied. Thus we use the government estimate of 53.5 billion VND for 93,917 ha of physical land to get the average land tax rate of VND 569,652 (Ha, 2016). Combined with the information on the farm-gate price, we get an average land tax rate of 95 kg paddy per physical land hectare or 50 kg paddy per planted land hectare. Here we use the conversion rate from a physical land hectare into a planted land hectare is about 1.9 for rice, based on the statistical yearbooks of GSO.

Since the government of Vietnam has gradually reduced the land tax rate since the early 2000s, we use this information to estimate the land tax rate for each year. In particular, the land tax rate is 50 kg/planted hectare in 2000–2001; 25 kg/planted hectare in 2002; 17.5 kg/planted hectare during 2003–2010 and 2.5 during 2011–2016. This estimation is made based on the following: land taxes reduced by 50 percent for land within the allocation limits and were free for poor households and households in communes classified as poor by the government in 2002 (Decision No.199/2001/QD-TTg dated 28 December 2001) (Prime Minister, 2001). Between 2003 and 2010, taxes were exempted for land within the allocation limits for all households (Resolution No.15/2003/QH11 dated 17 June 2003) (National Assembly, 2003). Since 2010, a further 50 percent reduction has been applied for land within accumulation limits (Resolution No.55/2010/QH12 dated 24 November 2010) (National Assembly, 2010).

Labor prices are drawn from VHLSS data sets from 2002 to 2016. They are average man-day wage paid for adult laborers on agricultural activities including land preparation, planting, tending, and harvesting. Prices are cross-checked with the data from rice production cost surveys carried out by the Department of Agricultural and Rural Development (DARD) in An Giang and Dong Thap provinces in the MRD between 2009 and 2014 (An Giang DARD, 2012–2014; Dong Thap DARD, 2009–2014).

The price of capital is the price of cattle as per Decision No.738/QD-TTg dated 18 May 2006 and Decision No.719/QD-TTg dated 5 June 2008.

The price of materials can be worked out using three sources of information. The first is that fertilizer accounts for about 60 percent of the total cost on materials, based on VHLSS data. The second is that we can calculate the price of fertilizer using VHLSS data, and therefore, we can find the value of materials. Finally, we get this value to divide by the quantity discussed earlier to get the price.

All price data in our research is in constant VND 2010 price and adjusted for regional and spatial differences (Appendix A).

Appendix C. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.worlddev.2021.105658.

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