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Can information constraints explain the low efficiency in premium quality rice cultivation? Evidence from smallholder farmers in Bangladesh

Christoph Kubitza[1] | Prakashan Chellattan Veettil[2] | Ishika Gupta[2] |
Timothy J. Krupnik[3]

[1]German Institute for Global and Area Studies (GIGA), Hamburg, Germany

[2]International Rice Research Institute (IRRI), New Delhi, India

[3]International Maize and Wheat Improvement Center (CIMMYT), Dhaka, Bangladesh

Correspondence
Prakashan Chellattan Veettil, Senior Agricultural Economist, IRRI, New Delhi, India.
Email: pc.veettil@irri.org

Christoph Kubitza, German Institute for Global and Area Studies (GIGA), Hamburg, Germany.
Email: Christoph.Kubitza@giga-hamburg.de

Abstract
The integration of smallholder farmers into emerging value chains for fine-grain and aromatic 'premium quality rice' (PQR) could prove to be crucial to improving rural livelihoods in Bangladesh, though efforts could be constrained by farmers' differing levels of agronomic knowledge. Based on a pre-analysis plan, we analyse farmers' ability to efficiently allocate production enhancing inputs in PQR cultivation based on a survey of 1420 farmers in key PQR producing areas. Farmers received a hypothetical budget to allocate to six different inputs advised for efficient production of PQR, mimicking familiar production decisions made seasonally on their own farms. Our results suggest that even without budget or input access constraints farmers tend to inefficiently allocate inputs in PQR in this hypothetical setting. In particular, they tend to overspend on seeds, fertiliser and pesticides. Farmers with better access to agricultural information, such as through PQR specific extension services, conversely reach substantially higher efficiency scores and decided to spend significantly less on fertiliser. Without future adjustments such as more targeted extension services, implied higher production costs will likely lower the profitability of PQR cultivation for smallholder farmers, thereby limiting potential income gains. Besides these economic concerns, excessive input use is associated with environmental externalities. Improved efficiency is therefore desirable from both an economic and environmental standpoint.

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1 | INTRODUCTION

The rapid transformation of food value chains opens up new opportunities to improve the livelihoods of smallholder farmers in low- and middle-income countries. However, these emerging markets also place substantial pressure on farmers to adapt their production practices (Reardon et al., 2009, 2014). Empirical literature already contains various case studies analysing the inclusion of smallholder farmers in food value chain transformations', as well as potential welfare gains. In particular, studies on modern agricultural value chains or high-value markets, and the role of food quality and safety, sustainability standards, and supermarkets have gained considerable traction (Chiputwa et al., 2015; Handschuch et al., 2013; Ola & Menapace, 2020). Although there are many positive examples, the evidence so far shows mixed results in terms of inclusion, welfare gains and efficiency (German et al., 2020; McCullough et al., 2008; Ros-Tonen et al., 2019). This suggests that potential welfare gains are highly context-specific, and it underscores the need for more rigorous studies to comprehend why smallholders cannot consistently reap the benefits from emerging high-value value chains.

In this study, we investigate the integration of smallholder farmers in premium quality rice (PQR) variety value chains that are newly emerging in markets in South Asia and Bangladesh in particular. The definition of PQR is not consistent across countries. In Bangladesh, however, rice with long, slender and fine grains, often with an aroma, such as basmati rice, are considered PQR (Mottaleb et al., 2017). PQR fetches higher prices than other rice varieties and allows for profit increases of up to 50% relative to coarse rice grains (CSISA, 2016). In addition, the total demand for PQR is expected to grow due to increasing per capita income, changing consumer preferences, and increasingly connected food supply chains (Mottaleb et al., 2017). Still, inadequacies in the PQR supply chain could limit potential economic gains, particularly among smallholder farmers, which threatens the potential positive effects for rural economic development.

It is widely documented that without access to requisite finance and information, farmers may inefficiently allocate resources, and without mechanisms to de-risk new investments in alternative varieties and emerging markets, they more slowly adopt new agricultural technologies (Duflo et al., 2011; Karlan et al., 2014). Yet, the reasons for low investment rates and high levels of inefficiencies of smallholder farmers often remain ambiguous due to the limited external validity of studies confined to specific settings, crops and technologies (Foster & Rosenzweig, 2010). In the case of Bangladesh, preliminary evidence suggests that poor knowledge of efficient input allocation, consequent under- or overspending on certain inputs, and associated low profitability are key constraints to increased PQR production among smallholders (CSISA, 2016).[1] Among others, such information constraints are frequently cited as a major obstacle in smallholder production systems.[2]

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[1] Efficient input allocation in PQR cultivation differs from non-PQR rice, in particular in fertiliser use.

[2] In South Asia, farmers face a host of constraints such as lack of access to information, input markets, credit, and insurances which forces them to invest less, or overinvest in easily available inputs (Brown et al., 2019; Bryan et al., 2014). In light of these market failures, policies have commonly focused on reducing risk through crop insurance schemes, increasing access to capital through microcredit or saving facilities, or improving information flow to farmers through extension services. Indeed, various studies suggest that the lack of insurance schemes and liquidity constraints hamper farmers' investments in agricultural intensification, particularly among risk-averse smallholder farmers (Karlan et al., 2014; Moser & Barrett, 2006). Other studies point to behavioural explanations such as present bias in decision making (Duflo et al., 2011). Some studies also argue that farmers are rational as actual returns to investment can be low or available inputs have low quality (Bold et al., 2017; Suri, 2011).

To substantiate this hypothesis with more rigorous analyses, we test, using an innovative survey module and a pre-analysis plan (Kubitza, 2020), if the lack of information on efficient allocation of agronomic inputs is a major constraint in PQR cultivation of smallholder farmers in Bangladesh. This hypothesis is rarely tested in the current literature. Using randomised controlled trials, numerous studies analyse the effects of information and communication technologies (ICT) or agricultural training on technology adoption, yield and household welfare (Aker et al., 2016; Ambler et al., 2017; Deichmann et al., 2016; Magruder, 2018; Ogutu et al., 2018). Other studies focus on the determinants of technical efficiency (Binam et al., 2004; Bravo-Ureta & Pinheiro, 1993; Seymour, 2017). However, only a few studies focus on allocative efficiency—the ability of farmers to more optimally allocate inputs given their prices. Clear evidence that links low allocative efficiency scores with the lack of information on improved production practices, but also other production constrains, is hence scarce.[3] Our findings are expected to contribute to the discussion on how low profitability in smallholder farming can be addressed with combinations of improved agronomic practices and information dissemination through extension, as well as what might be needed to de-risk investments in intensified crop production among smallholder farmers.

To address this issue, a survey module was designed to test the ability of smallholder farmers in Bangladesh to efficiently allocate a hypothetical budget to different inputs necessary for PQR cultivation. In the survey, farmers choose input levels mimicking production decisions familiar to them from their own farm. Efficient allocation was rewarded by higher payouts, while inefficient input allocation resulted in lower payouts. The survey module was designed to test if farmers are able to efficiently allocate their resources without being constrained by budget limitations, restricted access to inputs, or production uncertainty. The data allow to test if poor knowledge of production practices can explain inefficient allocation of inputs in PQR cultivation. We compare the decision with real world input allocation data from the same farmer. In total, the survey module was conducted with 1420 farmers in three districts of Bangladesh.

We find clear evidence that most smallholder farmers do not efficiently allocate inputs in PQR cultivation, even without facing budget and access constraints. The low efficiency is, however, caused in particular by overspending on seeds, fertiliser and pesticides. Farmers that received PQR extension services or have access to smartphones perform significantly better. Farmers that received PQR extension services spend, in particular, significantly less on fertiliser. We find similar patterns using real-world plot data. We conclude that the overspending on certain inputs and the associated increase in production costs severely limits the profitability of smallholder PQR cultivation in Bangladesh. Addressing the non-optimal input allocation of smallholder farmers could have substantial positive effects on rural incomes and poverty, as well as environmental outcomes.[4] Environmental benefits could occur due to optimised input allocation, and particularly in mitigating climate change. Global cereal production accounts for 50% of total global nitrogen fertiliser consumption, which causes substantial greenhouse gas (GHG) emissions (Ladha et al., 2016; Zhang et al., 2019); in Bangladesh, a comprehensive study has also identified inefficient fertiliser application and rice production as a primary driver of GHG emissions (Sapkota et al., 2021).

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[3]While we focus on information constraints, inefficient allocation of resources might also be affected by other factors. For instance, studies analyse inefficiencies in allocation of resources between individual and communal plots, or fields owned by different households members in sub-Saharan Africa (Guirkinger et al., 2015). As it is difficult to determine from observational data to what extent inefficiencies are due to rational behaviour, this literature draws also on field experiments that allow researchers to eliminate constraints common in real-world decisions and to compare between experimental and observational data (Apedo-Amah et al., 2020; Hoel et al., 2017).

[4]In Bangladesh, poverty is still widespread in rural areas with a poverty headcount of 26.7% versus 19.3% in urban areas in 2016 World Bank, 2019.

The study estimates GHG emissions for different agricultural land uses based on farm- and plot-level data and the scope of mitigation strategies based on expert interviews and existing evidence. The results show, firstly, that *aman* rice, which includes PQR, has the highest emissions per hectare, and that rice production, in general, is the most important source of emissions in the country, accounting for about 62% of total agricultural emissions. Secondly, the study suggests that improved nutrient use efficiency through better nitrogen (N) management could contribute to more than half of the total mitigation potential from the agricultural sector. To harness this mitigation potential, our results suggest that a significant contribution can be made by enhancing allocative efficiency of rice farmers. This involves, in particular, adjusting fertiliser application in PQR cultivation through improved access to information.

The remainder of this study is structured as follows: In Section 2, we explain the concept of allocative efficiency and its link with information constraints. In Section 3, we detail the design and implementation of the survey module, and Section 4 includes our three hypotheses. Section 5 reports our empirical specifications to test our hypotheses. Results are discussed in Section 6, and Section 7 concludes our study.

2 | ALLOCATIVE EFFICIENCY AND INFORMATION CONSTRAINTS

Growth in total factor productivity and its components, technical change, and technical and allocative efficiency, are often limited in low- and middle-income countries due to production constraints, in particular the lack of applicable information on improved production practices. Technical efficiency is understood as the ability of the farm to achieve the maximum output with constant inputs. In contrast, allocative efficiency measures the ability of farmers to optimally allocate inputs given their prices (Bravo-Ureta & Pinheiro, 1997). This implies that, in order to optimise their allocative efficiency and profit, farmers need to adjust the marginal product (MP) of each input to its price (MC) (Yotopoulos & Lau, 1973). Allocative efficiency is maximised with $MP_i = MC_i$ for each input i in order to produce one extra unit. Although it is often implicitly assumed that the input allocation is already at the most efficient level, the widely observed low profitability in low- and middle-income countries can be induced by both technical and allocative inefficiency.

Multiple studies analysed the link between total factor productivity in general and information access. Early studies focused primarily on the effect of farmers' education on technical efficiency. This includes studies that tested the effect of education on agricultural productivity while holding input levels constant (Azhar, 1991; Lockheed et al., 1980) or that examined the effect of information access on technical efficiency (Adhikari & Bjorndal, 2012; Binam et al., 2004). Another strand of literature focuses on experiments that address information constraints through using ICTs or extension services (Aker et al., 2016). These experiments change features of farmers' environment. Information experiments, in particular, modify the information available to farmers such as new information on economic returns or production practices. Through different interventions these studies narrow down what features of interventions affect specific agronomic and economic outcomes. While being the gold standard for establishing causality, such studies also have drawbacks.

First, they need baseline data and randomly assigned treatments and are as such often costly and only allow slow dissemination of results. Second, spillovers to non-treated farming households often confound treatment effects. This is especially the case for information experiments as information can be easily conveyed through social networks. However, robust randomisation strategies, such as using villages instead of households as the unit of treatment, can address this shortcoming. Lastly, while information constraints might

limit productivity and efficiency, easing these constraints through real-world interventions might not always affect the outcomes of interest. Other production constraints, such as limited budgets or access to inputs, might restrict the otherwise positive effects of new information on production practices. Decision experiments are an interesting alternative to these problems and can complement current research on information constraints. In our particular survey module, we ease constraints concerning budget, risk and access to inputs in order to assess if indeed limited information on best-practice input allocation affects allocative efficiency in PQR cultivation. Although our survey module does address the mentioned shortcomings, it comes also with certain drawbacks including potential hypothetical bias, limited real-world application due to multiple binding constraints, and the lack of concrete and testable treatment interventions. We discuss and address these shortcomings in Section 6 and the conclusion.

We assume that enhanced information or education allows for a more efficient assessment of the costs and gains of each single input inducing a reallocation of agronomic inputs. Addressing this issue, a few studies already attempted to decompose technical and allocative efficiency (Brümmer et al., 2002; Coelli et al., 2002; Henderson, 2015; Khan & Ali, 2013). A recent study also shows that specific information on agricultural practices was pivotal for the success of the New Rice for Africa (NERICA), a new group of rice varieties that yield best with specific cultivation practices. Farmers who received both NERICA and training were able to increase their yields by 23%. However, those who received NERICA but no training tended to experience a small decline in yield (ISPC, 2018). These limitations can also apply to the transformation of rice value chains in Bangladesh.

3 | SETTING AND SURVEY DESIGN

3.1 | Study setting and sample selection

Rice is the backbone of Bangladesh's agricultural economy and is grown in three seasons. In 2018, the harvested area across seasons was a little below 12 million hectares (FAOSTAT, 2020). In Bangladesh, most land area available for cultivation is already used. Although there is little scope to increase the harvested area, yields increased drastically from 2.5 tons/ha in 1990 to 4.7 tons/ha in 2018 across seasons (FAOSTAT, 2020). This success is largely due to the development of high-yielding and short-duration varieties but also increased use of irrigation and intensified nutrient management practices. Rice is also essential for national food security. Estimates of per capita rice consumption vary widely depending on data, but per capita estimates range from 386 to 538 g/day (Yunus et al., 2019).

With rice being central to the economy, changes in the agricultural value chain have far reaching consequences for producers and consumers. One major transformation currently underway is the shift from less expensive coarse rice to higher quality and specialty rice varieties (Bairagi et al., 2020; Minten et al., 2013). The quality of rice in Bangladesh is commonly judged by the shape and size of the kernel. Producers, traders and consumers often differentiate between coarse, medium and fine rice gains. The coarser the grain, the wider it is relative to the length (Minten et al., 2013). However, other traits such as transparency, milling, whiteness, percentage of broken grains and particularly aroma also play a role for quality assessments. Cross-country comparisons show high consumer preferences for rice attributes such as appearance and taste in South Asia (Bairagi et al., 2020). Overall, while the definition of fine-grained rice and PQR are not perfectly interchangeable, we use the literature on both because in Bangladesh, long, slender and fine grains with an aroma, such as basmati rice, are in general considered to be PQR (Mottaleb et al., 2017).

Minten et al. (2013) document that the demand for less expensive coarse rice is rapidly falling with a decline from 36% in 1999 to 17% in 2009 for total paddy sales at the producer level. Other studies suggest that PQR consumption, on the other hand, is continuing to increase in Bangladesh due to rising household income and changing food preferences (Bairagi et al., 2020; Mottaleb et al., 2017; Mottaleb & Mishra, 2016). Compared to the turn of the century, daily per capita consumption of fine grain rice increased by 33% in 2010 for average households belonging to the second and third expenditure quartiles (Mottaleb & Mishra, 2016). Responding to the increasing demand, it is estimated that rice farmers in Bangladesh grow more than 70 PQR varieties (CSISA, 2016). These include varieties such as Chinisagar, Basmati, Badshabhog, BRRI dhan 34, BRRI dhan 5, Kalizira, Tulsimla, BRRI dhan 37, BRRI dhan 38, BRRI dhan 50, BINA dhan12 and BINA dhan15 (Aziz & Kashem, 2017). Most of these varieties are grown during the monsoon '*aman*' season and several are traditional varieties. In 2002, it was estimated that 10% of all rice land was allocated to fine grain rice (International Development Enterprises, 2002; Minten et al., 2013). The World Bank (2007) conversely reported more conservative estimates with a share of 5% for fine-grained rice in total rice production. More recent numbers are scarce but studies on consumption patterns document an increase in fine-grained rice consumption (Mottaleb & Mishra, 2016).

In terms of agronomic considerations, PQR differs from non-PQR in several aspects. PQR yields are often lower compared to non-PQR due to the lack of short-stature varieties with a high harvest index, and a predominance of sub-optimal management methods among farmers (Aziz & Kashem, 2017; CSISA, 2016). PQR, however, is assumed to grow well under low levels of inputs. Output prices have also developed in favour of PQR—while PQR yield may be low, prices per kilogramme of grain are often higher than higher yielding coarse grain varieties (CSISA, 2016). While the price premiums for PQR over coarse rice was at 20% in the early 1980s, premium levels increased to almost 45% by 2009 (Minten et al., 2013).

For the present study, the districts Sherpur, Jhenaidha and Dinajpur in Bangladesh were purposively chosen due to high adoption rates of PQR among smallholder farmers. The sub-districts were also purposively selected based on the area of PQR cultivation. In the next step, 142 villages were randomly selected (32 in Sherpur, 38 in Jhenaidha and 72 in Dinajpur). A map of the districts and villages is provided in the Appendix F (Figure F1). The survey started in February 2020, and was temporarily suspended for 2 months due to COVID-19. Surveys resumed in July and were completed by mid-November 2020. In the selected villages, we conducted a census of all farmers, after which 10 households per village were randomly selected. For all treatments that address the potential hypothetical bias in our survey module on input allocation, a simple randomisation was implemented at the household level. We used the software *Surveybe* to conduct all interviews.

Following pre-testing and refinement, a structured questionnaire was administered face to face to a total of 1420 households. The questionnaire included information on individual household members, farm characteristics, off-farm income, marketing, household expenditures, as well as detailed plot-level information on farm inputs and yield. For each farm household, input and output data were only collected for the largest PQR and the largest non-PQR field managed by respondents. If a household managed more than two fields of equal size, the closest PQR and non-PQR fields to farmers' dwelling were selected.

3.2 | Survey design

The input allocation module used for our survey of 1420 farm households in 2020 was developed based on data from the 2016 Rice Monitoring System (RMS) survey in Bangladesh. The RMS survey, with a sample size of 1500 rice farmers, was conducted to monitor rice systems and capture varietal change over time. Based on the RMS data, a hypothetical

budget of USD 353 (BDT 30,000) was calculated, which is sufficient to purchase inputs (seeds, fertiliser, chemicals, irrigation, labour, machinery service and other required inputs) for one acre of PQR.[5]

In the next step, we used plot-level input and output data from RMS on rice production to calculate efficiency scores for different combinations of inputs. We applied a stochastic frontier approach. The stochastic frontier approach using a translog production function was modelled as follows:

$$\ln y_{iv} = \alpha_0 + \sum_m \alpha_m \ln X_{im} + \frac{1}{2} \sum_m \sum_n \alpha_{mn} \ln X_{im} \ln X_{in} + \varepsilon_{iv}, \text{ where } \varepsilon_{iv} = \vartheta_{iv} - u_{iv} \tag{1}$$

where y_{iv} is the rice yield achieved by respondent i in village v. X is a vector of the costs of applying six inputs chosen in the survey: seeds, fertilisers, herbicides applied or labour used for weeding, pest control products, irrigation, and other inputs. ε_{iv} is a composite error term: ϑ_{iv} constitutes noise (a symmetric distribution with zero mean and constant, finite variance) and u_{iv} depicts inefficiency (an asymmetric distribution with a positive expected value and finite variance). We assume that both terms are statistically independent and are also independent of inputs represented by X. Based on the extracted efficiency scores, we created different classes of payout for different combinations of inputs. Four types of efficiency classes were created: >85%, 75%–85%, 50%–75% and <50%.[6] Depending on irrigation availability, within each efficiency class, two types of average input combinations (for seed, fertiliser, weed management, pesticides, irrigation and other costs) were derived from the farmer production data. Thirteen agronomic management scenarios were developed and for each scenario a counterfactual was derived taking into account achievable efficiency gain by reallocation of inputs. The minimum average efficiency target was set as 80%. An average efficiency score of 90% or above was regarded as the highest efficiency class, yielding the highest attainable payout. With decreasing efficiency scores, lower payout levels were assigned (Appendix A).

3.3 | Survey implementation

Our survey module can be contextualised as an input allocation experiment related to agronomic management decision-making familiar to sampled rice farmers. The module was embedded within the household survey and took place under rules common to all respondents (Appendix B). The survey was conducted in the Bangla language by trained enumerators and was carried out at the home of the respondents, face to face with one participant and one enumerator. For each respondent, the survey module on input allocation began with a thorough explanation of the game. One trial with each respondent was then conducted to reduce potential misunderstanding. Each session combined with survey data collection lasted for 2 h on average.

Hypothetical bias, where farmers tend to behave differently when they face a hypothetical task compared to a real one (de-Magistris et al., 2013), is a major concern when inferring data collected in experimental situations to real-world settings. We implemented two different

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[5]An acre is about 0.405 ha. The average annual total income for our sampled farmers stands at USD 2834 (BDT 241,458), making the allocated budget approximately 12% of the farmers' yearly income.

[6]We opted for only four classes to streamline the survey game and capture common allocation patterns without introducing too much complexity. The simplification was necessary because the classes were calculated based on the RMS data and are therefore only a quite good, but not perfect, measure of allocation efficiency in our setting. A large set of classes would have resulted in a greater likelihood of discrepancies between the actual allocation efficiency and our survey module. Second, and more importantly, a game with dozens of classes would have been overly complex for participants.
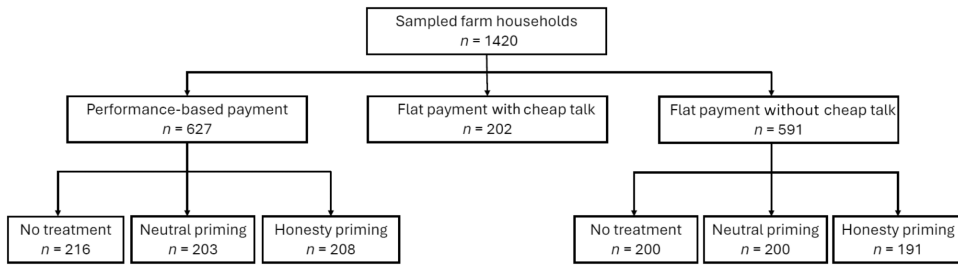
FIGURE 1 Flowchart delineating the different treatments. Two farmers with performance-based payment erroneously received the cheap talk treatment. Robustness checks showed that this did not affect our results.

measures to address this issue. First, we introduced a performance linked payout. A random subsample of farmers were told at the beginning of the survey module on input allocation that they would receive a payout depending on their performance in the game, while another fraction received a flat payment of USD 3.58. In total, 44% of the respondents received a performance-based payout. Second, to mitigate hypothetical bias, we applied an *ex-ante* calibration approach to stimulate farmers' motivation and honesty before the hypothetical game. Two approaches were followed here. One treatment consisted of a cheap talk script (Appendix C.1) that provided persuasive but non-binding information to incentivise farmers to reveal their true preferences, which was provided to farmers receiving a flat payment (Silva et al., 2011). In the second treatment, we used an honesty priming treatment *as ex-ante* calibration (de-Magistris et al., 2013). As priming can unconsciously affect people's behaviour, we exposed our respondents to particular words or cues connected to honesty in an unrelated task (Appendix C.2).[7] The questionnaire also contained a small section of mathematical test questions, which allowed us to estimate cognitive ability scores, and as such we control for potential heterogeneity in the level of understanding of the game. The distribution of these treatments is illustrated in Figure 1.

The actual survey on input allocation involved the following steps. The respondent received USD 358 of hypothetical money to invest either into different inputs necessary for the production of PQR on one acre of land or to save the money. To invest, farmers had to allocate part of their budget to different inputs for PQR cultivation. This mimicked production decisions familiar to them from their own farm. Farmers were allowed to save part of the money as it was not obligatory to invest the whole amount. Six different inputs were offered as described in Section 3.2. We assume here that all purchased inputs are used for PQR production and that no inputs were stocked or resold. To allocate resources, farmers assumed prices that they were facing at their farm mimicking the seasonal decisions during their own farming activities. The data hence proxy allocative efficiency: farmers' ability to optimally allocate inputs given their prices. By following a stochastic frontier analysis model based on estimated parameters of production function efficiency scores, a simple classification of yield and net profit for different input combinations was developed (Appendix A) and automatically calculated by the *Surveybe* program. If farmers over- or underinvested in certain inputs, efficiency decreased, as well as respective net profit. For farmers receiving a performance-based cash incentive, payout also decreased. Farmers could obtain a real payout between USD 2.99 and 7.16. Farmers that were not selected to receive a performance-based cash incentive received a fixed amount of USD 3.58.

For the sake of simplicity, performance-based payouts did not directly depend on the amount of money saved. Rather, farmers had to initially decide to invest and to face a payoff

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[7]Respondents were provided with one word and had then to choose three synonyms from a list of six other words. The task was repeated eight times. The meanings of the words were related to honesty (Appendix C.2).

ranging between USD 2.99 and 7.16 equivalent, or to opt out of the survey, receiving only a nominal participation fee. This option, however, was not chosen by any farmer participant. Yet, spending all the money in the investment process was not the optimal choice. If respondents overinvested in certain inputs, efficiency decreased and hence payout also decreased. In other words, respondents had to save part of the budget in order to receive the maximal payout. Respondents also received a specific warning at the beginning of the game: while underspending reduces yield and payout, overspending on any particular input also decreases payout.

4 | HYPOTHESES

The survey module was designed to analyse whether inefficient allocation of inputs affects PQR production of smallholder farmers and if information constraints in particular lead to low allocative efficiency. To address the research question, we test three separate hypotheses. Hypotheses were designed before accessing the dataset, and a pre-analysis plan was registered (Kubitza, 2020).[8]

> **H1.** Input allocation patterns mimic non-PQR cultivation practices and indicate major information constraints. That is, the average allocative efficiency score in PQR cultivation obtained in the decision experiment does not belong to a high efficiency class.

> **H2.** Factors related to information access affect allocative efficiency scores. High efficiency scores in the decision experiment are positively correlated with real-world adoption of PQR, access to extension services, mobile phone ownership, and membership in farmer organisations.

> **H3.** Farmers' efficiency scores in real-world PQR cultivation are lower compared to efficiency scores obtained from the decision experiment. The difference in scores can be explained by other constraints such as limited access to credit.

5 | EMPIRICAL SPECIFICATIONS

5.1 | Hypothesis 1

In the survey module on input allocation, farmers' input allocations were directly aligned to efficiency scores that were derived from the RMS survey. Input allocations were ordered according to their efficiency into four classes with an average efficiency of 0.4, 0.6, 0.8 and 0.9 (see Appendix A for more details). Based on these results, we assess if farmers efficiently allocate inputs in PQR production using simple descriptive statistics.

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[8]Three changes in the selection of variables and the specification occurred with regard to the pre-analysis plan. First, the measurement of the GPS coordinates was too imprecise due to errors in the data recording, preventing a precise calculation of distances between farmers within the villages. We hence had to exclude the variable that measured the effect of neighbouring PQR farmers. Second, to address omitted variable bias, we included a variable that proxies farmers' general interest in PQR cultivation through asking them how much land they would hypothetically dedicate to PQR. Third, we opted to use ordered logit instead of Tobit models as they better match our outcome variable. Our conclusions are, however, not affected by these changes. The results from the initial specification are available on request from the authors.

5.2 | Hypothesis 2

Allocative efficiency scores are a function of observable variables related to information constraints. As input allocations were ordered according to their efficiency into four classes with an average efficiency (see Appendix A), OLS (ordinary least square) estimates can be inconsistent. To address this concern, we used ordered logit as well as OLS models with standard errors clustered at the village level. The regression model is specified as follows:

$$u_{ivu} = \beta_1 Ex_{ivu} + \beta_2 PQR_{ivu} + \beta_3 \mathbf{CP}_{ivu} + \beta_4 VPQR_{vu} + \beta_5 \mathbf{C}_{ivu} + \tau_u + \omega_{ivu} \tag{2}$$

where u_{ivu} is the elicited efficiency class from the module on input allocation of farm household i in village v in sub-district u. Ex_{ivu} is a dummy for access to extension services of farm household i. PQR_{ivu} is the adoption of PQR varieties of farm household i. CP_{ivu} includes dummies if the household owns a mobile phone, if the household owns a smartphone, if the household is a member of a farming-related organisation and if the household is a member of an organisation unrelated to farming. $VPQR_{vu}$ is the share of farmers that adopted PQR in village v based on census data. C_{ivu} includes further control variables such as age of the household head, whether the household is female headed, educational level of the household head, religion of household head, number of adults in household, total farm size, whether farming is the main occupation and annual household consumption expenditure. We also include the maximum attainable yield for rice cultivation at village level based on data from the Global Agro-Ecological Zone (GAEZ) database to control for any differences in agroecological suitability. τ_u includes location dummies for the 12 different sub-districts in which games were administered. These spatially explicit variables control for agroecological as well as structural variation between regions. These variables also control for differences between responses before and after the COVID-19 pandemic, as timing of the interviews correspond to the location of the households. Variables are defined in detail in Appendix D.

5.3 | Hypothesis 3

The difference between the hypothetical efficiency scores and observational plot-level efficiency scores are a function of observable variables related to production constraints. We calculate the costs of each production enhancing input of the largest PQR plot of each farmer. Efficiency scores are then assigned based on the same rules as in the module on hypothetical input allocation (Appendix A). Naturally, the sample only includes PQR plots. We again use a set of observables variables to explain the gap between both efficiency scores using both ordered logit and OLS models. To estimate differences between both these efficiency scores, we estimate a regression of the following type:

$$\partial_{piv} - u_{ivu} = \beta_1 Ex_{ivu} + \beta_2 PQR_{ivu} + \beta_3 \mathbf{CP}_{ivu} + \beta_4 VPQR_{vu} + \beta_5 \mathbf{C}_{ivu} + \beta_6 \mathbf{Cr}_{ivu} + \tau_u + \omega_{ivu} \tag{3}$$

where ∂_{pivu} is the efficiency score obtained from observational plot data and u_{ivu} the efficiency score obtained from the module on input allocation. We include the same control variables as in Equation (2). Cr_{ivu} includes two proxies measuring credit access: access credit in general and access to credit from a bank.

TABLE 1   Validation of the hypothetical input allocation.

	(1)	(2)
	Efficiency score	Efficiency score
Cash incentive (=1)	0.886	0.837
	(0.110)	(0.115)
Cheap talk (=1)	0.748*	0.756
	(0.119)	(0.129)
Honesty priming (=1)	1.062	1.080
	(0.108)	(0.111)
Price of modern PQR (USD/kg)	0.712	0.683
	(0.377)	(0.366)
Cognitive score	1.232***	1.227***
	(0.079)	(0.073)
Additional controls	No	Yes
Wald χ^2	14.195	129.438
Pseudo-R^2	0.009	0.057
Observations	1416	1414

Note: PQR stands for premium quality rice. Ordered logit models used for all regressions. Additional controls include all control variables specified in Equation (2). Dependent variables are efficiency classes derived from the hypothetical input allocation. Odds ratios with standard errors clustered at village level in parentheses are reported.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

6 | RESULTS AND DISCUSSION

6.1 | Data validation

To address potential hypothetical bias or social desirability, we provided three treatments to randomly chosen sub-groups of farmers: a performance-based cash incentive, a cheap talk, and an honesty priming treatment.[9] We then compared the hypothetical efficiency scores of treatment famers with those who did not receive any treatment (control farmers). We then used an ordered logit model to determine if there are any statistically significant differences between the treated and control farmers.

We do not find any significant changes for farmers that received a cash incentive for their performance during the survey (Table 1).[10] We also did not find any difference for honesty priming. We only found, for the group of 204 participants to whom a cheap talk script was administered, lower efficiency scores during the survey, but only in small magnitude and weakly significant. In addition, the direction is contrary to the expectation that a cheap talk script increases the motivation and performance of participants. Furthermore, the effect turns insignificant when we control for other variables; this makes us confident that our results are not affected by the hypothetical scenario. We also tested if the likelihood of reaching the highest efficiency class is affected by any treatment. We found no significant effects (see Table E3 in Appendix E). That is, the attribution of efficiency due to

[9]We test the validity of the randomisation by comparing age, farm size, education, consumption expenditure and PQR share of rice cultivation of treated and non-treated farmers. Results are reported in Table E1 in Appendix E. We only find a significant effect of PQR cultivation on the likelihood of receiving the cheap talk script. We opted therefore to use a large set of control variables for the model in column (2) in Table 1.

[10]Descriptive statistics on the number of treated farmers and average efficiency scores are reported in Table E2 in Appendix E.

hypothetical bias or social desirability is negligible, and farmers' investment behaviour can be linked to information and prior experience with PQR, as well as the smoothening of budget constraints.

If the survey was not properly understood by some specific groups of farmers and their impaired understanding correlates with potentially influential characteristics of the farming household, a consistent analysis could also be impaired. However, detailed pre-testing was done and the decisions in the survey were validated using focus group discussions at five different locations. The experiment was simplified such that it was easily understandable to farmers and thoroughly explained during implementation. In particular, one training session was conducted to facilitate understanding of the survey module on input allocation. This could have led to learning effects with farmers improving their efficiency scores. However, we found that input allocation was qualitatively similar between the training session and the actual survey. We report the results of the training session in Table E4 in Appendix E.

Farmers, however, increased their spending on fertiliser and pesticides, presumably in an attempt to increase their low efficiency scores during the training sessions. Still, cognitive abilities could influence the ability to understand the survey module on input allocation as well as efficient decision-making in farming. To address this concern, we tested if elicited cognitive ability (using math scores) affects efficiency scores in the input allocation module. Table 1 shows that the cognitive scores have a highly significant positive effect on the efficiency scores. To avoid omitted variable bias, we include farmers' cognitive score in all regression models onwards.

6.2 | Main results

We converted all results to hectare and USD using the official exchange rate (period average 2020) for Bangladesh (World Bank, 2022).[11] Our results show that farmers own on average 0.6 hectare of land (Table 2). During the *aman* season of 2019, 68% of surveyed farmers cultivated PQR. Interest in PQR cultivation seems to be high in general; farmers indicated that they would on average cultivate 66% of their rice land with PQR in a hypothetical scenario. About 48% of surveyed farmers received information on PQR through extension services; 38% received such services through the Department of Agricultural Extension, while 22.5% received advice through private channels such as dealers. A significant share received extension services from both governmental and private sources. NGOs, radio, TV and mobile phones were less relevant with a share of less than 2% each. Only a small share of farmers were members of farm organisations (3.6%). Although PQR yields a price premium in the market with 0.49 USD/kg versus 0.21 USD/kg for non-PQR, yield is very low as expected. On average, PQR plots yield 2.5 tons/ha while non-PQR plots yield close to 5 tons/ha.

6.2.1 | Hypothesis 1

Panel a in Figure 2 shows that most farmers only reach low efficiency scores, confirming our first hypothesis. The lowest class of 0.4 is attained by 58% of farmers, while around 18% reached 0.5 and 0.8, respectively. Only about 5% reach the maximum score of 0.9. Farmers overspent especially on seeds and fertiliser (Table 2). They allocated 32 USD/ha to seeds while

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[11]Official exchange rate (BDT per USD, period average 2020) for Bangladesh: 84.87 BDT/USD.

TABLE 2 Descriptive statistics.

	Obs.	Mean	Std. dev.
Seeds (USD/ha)	1420	31.913	20.849
Fertiliser (USD/ha)	1420	115.448	59.569
Herbicides/weeding (USD/ha)	1420	31.680	32.869
Pesticide (USD/ha)	1420	93.391	62.792
Irrigation (USD/ha)	1420	47.673	41.443
Other costs (USD/ha)	1420	373.264	107.713
Age of household head	1418	47.173	12.402
Female headed household (=1)	1418	0.003	0.053
Education of household head (years)	1418	5.927	4.550
Muslim household head (=1)	1420	0.889	0.314
Number of adults	1418	3.399	1.359
Own cultivated land (ha)	1420	0.605	0.804
Farming main occupation (=1)	1420	0.582	0.493
Cultivated PQR in *aman* season (=1)	1420	0.682	0.466
Intended share of rice land with PQR (0–100)	1420	66.508	34.620
Received PQR extension service (=1)	1420	0.482	0.500
Member of any farm organisation (=1)	1420	0.036	0.186
Member of any non-farm organisation (=1)	1420	0.235	0.424
Household consumption exp. (log)	1420	11.564	0.537
Smartphone ownership (=1)	1420	0.482	0.500
Mobile phone ownership (=1)	1420	0.947	0.224
Cognitive score	1420	4.542	1.220
Share of PQR farmers in village (0–1)	1420	0.455	0.308
Maximum attainable yield of rice	1420	5733.123	73.935
Surveyed after COVID-19 pandemic (=1)	1420	0.493	0.500

Note: PQR stands for premium quality rice. Two households have incomplete household roster data, leading to their exclusion from subsequent analysis.

to reach the highest efficiency class, they should spend less than 14.56 USD/ha. For fertiliser, they also spend 115 USD/ha on average, while they should spend less than 101.92 USD/ha to reach the highest efficiency class (see Appendix A). They also spent a substantial amount of the budget on pesticides at 93.39 USD/ha. The major part of the budget, 373.26 USD/ha, however, was spent on other costs, which include all necessary labour costs and further production steps such as harvesting.

The high expenditure on fertiliser in the survey could reflect the agronomic practices from farmers' experience cultivating non-PQR. For aromatic *aman* rice (such as BRRI 34, BRRI 37, BRRI 38), the recommended minimal fertiliser combination is 49–9–41 kg/ha of N-P-K for low soil quality. For non-aromatic *aman* rice varieties (such as BRRI 11, BRRI 22, BRRI 40 and BRRI 41, among others), the recommended fertiliser combination is substantially higher with 61–11–51 kg/ha of N-P-K (BARC, 2018). In some settings, studies suggest that increasing fertiliser dosage does not significantly increase yields of aromatic varieties, and that any response to N application levels out earlier than with non-aromatic varieties (Aziz & Kashem, 2017). Based on farm trials on four aromatic rice varieties in Senegal, Koffi et al. (2016) show that while rice yields rise with increasing nitrogen input at low levels, fertiliser partial factor
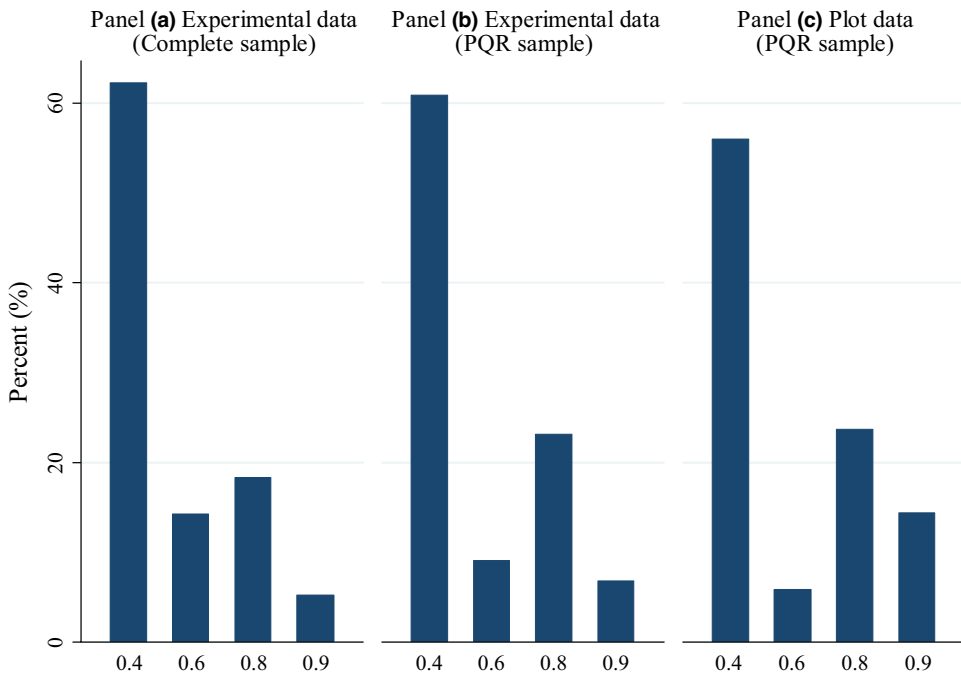
FIGURE 2 Distribution of efficiency classes. PQR stands for premium quality rice. Frequency measure is cut off at 60%. Panel (a) shows efficiency scores from the hypothetical input allocation ($N = 1420$). Panel (b) shows efficiency scores from the hypothetical input allocation for the subsample of PQR farmers ($N = 527$). Panel (c) shows the respective efficiency scores from real-world plot data for the subsample of PQR farmers ($N = 527$).

productivity decreases progressively with incremental levels of nitrogen from 60 to 150 kg/ha. Although response functions to fertiliser are highly context- and genotype-specific, low fertiliser recovery efficiency in fine grain rice at high input levels is relatively well documented (Emran et al., 2019; Oo et al., 2007; Shivay et al., 2016) and decreases in partial factor productivity could be even more steep compared to other varieties. This suggests that the low efficiency scores observed in our data could partly reflect a lack of knowledge on appropriate cultivation practices for PQR among farmers.

6.2.2 | Hypothesis 2

We hypothesised that allocative efficiency scores are a function of observable variables related to information constraints (Equation 2). Using ordered logit regressions, results show that farmers who indicated that they would cultivate a larger share of their land with PQR obtained significantly higher efficiency scores (Table 3, columns 1 and 2). This could reflect farmers' general interest in PQR. Farmers that have access to smartphones also reached significantly higher efficiency scores, which could reflect the effect of better access to information. Farmers that received advice on PQR cultivation reach significantly higher efficiency scores as well.[12]

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[12]While we find consistent positive effects of variables related to information access, we also find substantial variation in the effects between the different districts (Table E5 in Appendix E). We attribute this to differences in PQR cultivation, agricultural productivity and poverty. Dinajpur and Sherpur are home for traditional aromatic rice (>15% rice area in *aman* season), whereas expansion in Jheneidah is low (~3%) and mostly new PQR varieties such as BRRI dhan 50 are common. Dinajpur district is especially poor compared to the two other districts (World Bank, 2019). Table E5 in Appendix E suggest that enhanced extension services are especially important in settings with limited financial resources at the farm level (private capital).

TABLE 3 Determinants of allocative efficiency and input use in the hypothetical input allocation.

	(1)	(2)	(3)	(4)	(5)
	Ordered logit	OLS			
	Efficiency score	Efficiency score	Fertiliser (USD/ha)	Herbicide/weeding (USD/ha)	Pesticide (USD/ha)
Received PQR extension service (=1)	1.304*	0.025**	−11.831***	3.810	−1.168
	(0.203)	(0.012)	(3.729)	(2.986)	(3.507)
Member of any farm organisation (=1)	1.427	0.027	6.126	10.405	−13.712*
	(0.442)	(0.031)	(10.255)	(6.799)	(7.526)
Smartphone ownership (=1)	1.320**	0.022**	−0.611	−5.680***	−4.222
	(0.174)	(0.011)	(2.899)	(2.133)	(2.634)
Mobile phone ownership (=1)	0.707	−0.024	10.285*	1.625	−3.038
	(0.191)	(0.023)	(5.848)	(3.571)	(6.422)
Cultivated PQR in *aman* season (=1)	1.222	0.017	−2.095	−4.490	9.894**
	(0.304)	(0.021)	(6.531)	(5.807)	(4.872)
Age of household head	1.004	2.E-4	−0.005	0.124*	−0.385***
	(0.005)	(4.E-4)	(0.125)	(0.073)	(0.115)
Female headed household (=1)	0.255	−0.115	91.910**	17.424*	−21.717
	(0.424)	(0.097)	(35.702)	(10.061)	(19.550)
Education of household head (years)	0.997	−3.E-4	−0.613	0.190	−0.363
	(0.016)	(0.001)	(0.370)	(0.222)	(0.294)
Muslim household head (=1)	1.243	0.016	6.198	3.937	6.965
	(0.355)	(0.021)	(4.305)	(4.257)	(6.247)
Number of adults	1.011	0.001	1.333	2.114***	0.827
	(0.048)	(0.004)	(1.262)	(0.763)	(0.959)
Own cultivated land (ha)	1.000	7.E-6	−5.210***	−0.531	1.334
	(0.000)	(2.E-5)	(1.864)	(0.895)	(1.537)
Farming main occupation (=1)	0.946	−0.004	2.349	−3.262	7.023**
	(0.137)	(0.012)	(3.280)	(2.271)	(3.024)
Intended share of rice land with PQR (0–100)	1.005*	4.E-4*	−0.085	0.028	−0.022
	(0.003)	(2.E-4)	(0.097)	(0.075)	(0.060)
Member of any non-farm organisation (=1)	0.815	−0.016	4.225	−1.080	−3.976
	(0.127)	(0.013)	(3.822)	(3.432)	(3.622)
Household consumption exp. (log)	0.746**	−0.028**	4.281	−4.789**	7.738**
	(0.107)	(0.011)	(3.558)	(2.358)	(3.038)
Cognitive score	1.216***	0.016***	−0.710	−0.564	−0.479
	(0.075)	(0.005)	(1.497)	(1.116)	(1.395)
Share of PQR farmers in village (0–1)	0.575	−0.030	0.393	−15.383*	3.246
	(0.203)	(0.026)	(11.289)	(8.811)	(7.669)
Maximum attainable yield of rice (kg/ha)	0.994	−2.E-4	−0.144	−0.044	−0.053
	(0.004)	(2.E-4)	(0.146)	(0.110)	(0.060)

(Continues)

TABLE 3 (Continued)

	(1)	(2)	(3)	(4)	(5)
	Ordered logit	**OLS**			
	Efficiency score	**Efficiency score**	**Fertiliser (USD/ha)**	**Herbicide/weeding (USD/ha)**	**Pesticide (USD/ha)**
Constant		2.306	891.235	329.201	363.183
		(1.406)	(849.285)	(640.056)	(351.032)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes
Wald χ^2/F-statistic	118.637	5.961	9.845	3.385	27.304
Pseudo-R^2/R^2	0.055	0.121	0.318	0.143	0.491
Observations	1418	1418	1418	1418	1418

Note: PQR stands for premium quality rice. Ordered logit models used for column 1, OLS for columns 2–5. Odds ratios for column 1 and marginal effects for columns 2–5 are reported. Standard errors clustered at village level are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Most of the other variables do not show any consistent and significant effect except for the cognitive score and households' consumption expenditure. Overall, our results suggest that access to information and previous experience strongly determine allocative efficiency, which confirms our second hypothesis. Omitted variables could bias our estimates; we control, however, for a large set of variables to limit this potential bias.

Overspending on fertiliser could be a major limitation for efficient PQR cultivation that could be addressed by agricultural extension services (Table 2). Indeed, farmers that received advice on PQR appropriate cultivation spent significantly less on fertiliser in the module on hypothetical input allocation, with an average decrease of 12 USD/ha (Table 3, column 3). We did not find any significant effects of extension services on any other input used in PQR production (Table 3 and Table E6 in Appendix E). In addition, based on the RMS survey, we calculated for each efficiency class and input allocations a potential counterfactual. This counterfactual had similar total costs, but with an optimal allocation of inputs as documented in Appendix A and Table E7 in Appendix E. Our results again confirm that substantial savings in resources are possible by increasing allocative efficiency. Fertiliser expenditures in the data were 115.45 USD/ha, while they would have been only at 72.80 USD/ha in the optimised scenario. Pesticide expenditures could have been reduced even more substantially from 93.39 to 16.02 USD/ha, or perhaps even further if farmers incorporated integrated pest management techniques that we did not account for in this study. However, unlike for fertiliser use we cannot relate pesticide expenditures to any particular variable related to information access. As reported in Table E4 in Appendix E, the input allocation between the training round and the actual round was qualitatively similar. In addition, we conducted an additional robustness check using the same models as in Table 3 and the data from the training round (Table E8 in Appendix E). The results support our conclusions.

6.2.3 | Hypothesis 3

We hypothesised that we could explain the difference between farmers' efficiency scores in real-world PQR cultivation and efficiency scores obtained from the hypothetical input allocation. We only used data from farmers that actually cultivate PQR in the monsoon *aman* 2019 season, who bought seeds in the market and spent less than 353 USD (30,000 BDT) on

TABLE 4 Comparison between hypothetical input allocation and real-world plot data.

	Input allocation data		Plot data	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**
Seeds (USD/ha)	31.940	22.859	35.994	36.911
Fertiliser (USD/ha)	98.676	46.084	74.106	36.911
Herbicides/weeding (USD/ha)	27.313	29.097	28.822	31.648
Pesticide (USD/ha)	112.472	67.582	59.199	43.944
Irrigation (USD/ha)	32.038	26.782	19.774	32.725
Other costs (USD/ha)	356.076	101.540	395.321	139.863
Efficiency scores	0.552	0.193	0.579	0.211

Note: 527 observations.

all inputs. As expected, efficiency scores from real-world data and the hypothetical input allocation are significantly and positively correlated. Surprisingly, the average efficiency scores from the plot data are significantly larger compared to the data from the hypothetical input allocation, but the magnitude is small with 0.027 (see Table 4). Based on these results, we suggest that overspending on fertiliser and seeds appears to lead to low efficiency scores in both scenarios. These farmers were usually assigned the lowest possible efficiency class. However, overspending on inputs was more severe in the hypothetical input allocation module when budget limitations were not imposed. This indicates that interventions that ease farmers' budget constraints could have adverse negative consequences if not tempered with appropriate technical advice, as farmers allocated the additional resources to fertiliser, which resulted in decreased efficiency and lower profitability (Figure 2, Panel b and c). Table 5 shows for our subsample of PQR farmers that the effect of PQR extension service is positive and of similar size as in Table 3 for efficiency scores from the hypothetical input allocation module and plot data, though it is not significant. This could be potentially due to the smaller sample size. The effect sign of most other variables are also similar to our initial results, but insignificant with the exception of smartphone ownership. Based on Equation (3), we did not find that any variables consistently and significantly explained the difference between the efficiency scores of the data from the hypothetical input allocation and the plot data (Table 5, column 3). The significant and positive effect of smartphone ownership was, however, associated with higher efficiency scores in the hypothetical input allocation.

7 | CONCLUSION

In this study, based on a pre-analysis plan, we tested the hypothesis that smallholder farmers inefficiently allocate inputs in PQR cultivation due to information constraints. This hypothesis was confirmed. Employing a survey module on hypothetical input allocation, we observed that farmers tend to overspend on seeds, but also on fertiliser and pesticides, although budget and access constraints were not binding in decision making. The higher production costs lower the profitability of PQR cultivation and limit potential income gains. Besides economic concerns, excessive fertiliser input use is associated with greenhouse gas emissions in flooded rice culture (Ladha et al., 2016; Sapkota et al., 2021; Zhang et al., 2019).

We tested if factors related to information access can increase allocative efficiency scores. In some study areas, farmers who have access to smartphones, who join farmer organisations or have sufficient prior experience in cultivating PQR reached higher efficiency scores. Farmers who have received PQR specific extension information also reached substantially

TABLE 5 Determinants of allocative efficiency (PQR farmer subsample).

	(1)	(2)	(3)
	Input allocation data	**Plot data**	**Difference in efficiency**
Received PQR extension service (=1)	1.312	1.352	1.023
	(0.343)	(0.273)	(0.224)
Member of any farm organisation (=1)	1.207	1.067	0.901
	(0.683)	(0.571)	(0.304)
Smartphone ownership (=1)	1.382**	0.818	0.629***
	(0.195)	(0.138)	(0.096)
Mobile phone ownership (=1)	1.009	0.698	0.702
	(0.414)	(0.242)	(0.232)
Age of household head	0.989	0.997	1.003
	(0.008)	(0.009)	(0.010)
Education of household head (years)	0.975	1.023	1.042
	(0.017)	(0.040)	(0.040)
Muslim household head (=1)	1.342	0.782	0.645**
	(0.567)	(0.174)	(0.118)
Number of adults	1.020	1.097**	1.078
	(0.043)	(0.047)	(0.050)
Own cultivated land (ha)	1.000	1.000	1.000
	(0.000)	(0.001)	(0.001)
Farming main occupation (=1)	1.085	1.156	1.046
	(0.215)	(0.232)	(0.281)
Intended share of rice land with PQR (0–100)	1.001	0.993	0.993
	(0.008)	(0.005)	(0.006)
Member of any non-farm organisation (=1)	1.111	0.809	0.795
	(0.225)	(0.208)	(0.149)
Household consumption exp. (log)	0.726	0.791	1.063
	(0.167)	(0.129)	(0.209)
Cognitive score (1–6)	1.119	1.044	0.950
	(0.077)	(0.099)	(0.058)
Share of PQR farmers in village (0–1)	1.601	0.485	0.437
	(1.427)	(0.350)	(0.330)
Maximum attainable yield of rice (kg/ha)	0.998	0.987**	0.991
	(0.011)	(0.006)	(0.006)
Access to credit (=1)	0.667***	0.818	1.189
	(0.093)	(0.163)	(0.274)
Access to credit from bank (=1)	1.218	1.450	1.089
	(0.218)	(0.415)	(0.301)
Sub-district fixed effects	Yes	Yes	Yes
Wald χ^2	69.566	71.577	41.561
Pseudo-R^2	0.065	0.065	0.023
Observations	525	525	525

Note: PQR stands for premium quality rice. Ordered logit models used for all regressions. Odds ratios with standard errors clustered at sub-district level in parentheses are reported.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

higher efficiency scores. Those who received PQR specific extension services also tended to spend significantly less on fertiliser. Using data from farmers' own cultivation practices, we found that real-world efficiency scores were not substantially better or worse than the efficiency scores from the hypothetical input allocation. We therefore conclude that a major fraction of the observed inefficiency in input allocation can be attributed to pure information constraints. However, less overspending occurs also in the real-world data. Limited budgets could have constrained the overspending on inputs, and the difference between the efficiency scores from real world data and hypothetical allocation data are not associated with any of the relevant variables. This is, however, not surprising considering that the obtained scores are fairly similar.

Besides contributing to our understanding of smallholder farmers' integration in high-value chains, our study illustrates the potential of hypothetical input allocation data to assess the extent of information constraints in smallholder production. Our approach suggests that extension services have to be more sensitive to allocative efficiency, and that they must be focused on core messaging on input use efficiency as related specifically to PQR varieties. Measuring the success of extension services only by technology adoption or yield may not always capture the full range of impacts. Opening the black box of information constraints may hence be useful in this regard. A recent study emphasises that current efforts to design information interventions would benefit from detailed groundwork including assessing the actual need of specific information (Aker et al., 2016).

Our study, however, involves several caveats. First, our identification strategy for causal effects is limited. Although we controlled for a large set of observable variables at the household level as well as location fixed effects, we could not completely rule out that unobservable characteristics influence both efficiency scores and key variables such as access to extension services. And due to low intra-village variation of our key variables, we were not able to use villages as fixed effects. Second, we focused mainly on information constraints. Although this contributes to the literature on information constraints in smallholder rice production, we were not able to evaluate if other interventions such as improved access to input markets, timing of input availability, quality of inputs, or alternative forms of knowledge such as integrated nutrient or pest management may have proven to be more important in the context of the study. Lastly, farmers made decisions based on their status quo condition, with reference to access to input markets primarily. Still, based on the evidence of our study, we suggest that addressing information constraints in efficient input allocation can contribute to the integration of smallholders in high-value market chains such as represented by PQR.

Our results have important policy implications. Although the effects of agricultural growth have become less poverty reducing over time in Bangladesh, poverty is still widely spread in many rural areas of Bangladesh with a poverty headcount of 26.7% in 2016 (World Bank, 2019). Such information can and should motivate interventions that focus on PQR cultivation in smallholder systems, including more concerted action to improve farmers' input allocation. Otherwise, low yields and plot profitability could eventually slow down smallholder participation in high-value market chains. Addressing the nonoptimal input allocation—particularly the overspending on fertiliser—could have hence substantial positive effects on farm incomes but also broader environmental co-benefits. In particular, farmers in our study appeared to believe that more fertiliser is associated with higher yield and profitability. Part of this notion is likely tied to the prior campaigns that promoted the use of chemical fertiliser and pesticides with inadequate focus on input use efficiency and appropriate agronomy (Rahman & Zhang, 2017). Adjusting these perceptions is in particular important considering that fertiliser prices in Bangladesh are subsidised and held consistent in most years, making it comparably cheap input (Ahmed et al., 2021). Recalibrating this widely held belief should be part of future extension efforts.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Christoph Kubitza https://orcid.org/0000-0002-2697-3535
Prakashan Chellattan Veettil https://orcid.org/0000-0002-2125-0178
Timothy J. Krupnik https://orcid.org/0000-0001-6973-0106

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APPENDIX A

Pay-off matrix

	Seeds	Fertliser	Herbicide	Pesticide	Irrigation	Othercosts	Yield	Efficiency	Avg. EFF	Payment
Scenario 1	<500	≤3500	≥0	≥0	≥1000	≥0	2.4	>85%	0.90	600
Counterfactual 1	400	2850	300	1000	750	12,000	2.4	>85%	0.90	
Scenario 2	<500	≤3500	≥0	≥0	0–999	≥0	2.2	>85%	0.90	600
Counterfactual 2	450	3000	50	500	0	11,600	2.2	>85%	0.90	
Scenario 3	<500	>3500	≥0	≥0	≥1000	≥0	2.3	75%–85%	0.80	500
Counterfactual 3	400	2850	300	1000	750	12,000	2.4	>85%	0.90	
Scenario 4	<500	>3500	≥0	≥0	0–999	≥0	2.2	75%–85%	0.80	500
Counterfactual 4	400	2850	300	1000	750	12,000	2.4	>85%	0.90	
Scenario 5	500–800	≤3500	≥0	≥0	≥0	15,000–18,999	2.1	75%–85%	0.80	500
Counterfactual 5	450	3000	50	500	0	11,600	2.2	>85%	0.90	
Scenario 6	500–800	≤3500	≥0	≥0	≥0	0–14,999	2.0	75%–85%	0.80	500
Counterfactual 6	450	3000	50	500	0	11,600	2.2	>85%	0.90	
Scenario 7	500–800	>3500	≥0	≥0	≥3000	≥0	2.4	50%–75%	0.60	375
Counterfactual 7	400	2850	300	1000	750	12,000	2.4	>85%	0.90	
Scenario 8	500–800	>3500	≥0	≥0	0–2999	≥0	2.2	50%–75%	0.60	375
Counterfactual 8	400	2850	300	1000	750	12,000	2.4	>85%	0.90	
Scenario 9	500–800	≤3500	≥0	≥0	≥0	≥19,000	1.8	50%–75%	0.60	375
Counterfactual 9	450	3000	50	500	0	11,600	2.2	>85%	0.90	
Scenario 10	>800	≥0	≥0	≥0	>3000	≥0	1.5	<50%	0.40	250
Counterfactual 10	450	2100	400	1500	700	13,300	2.2	75%–85%	0.80	
Scenario 11	>800	≥0	≥0	≥0	1–3000	≥0	1.3	<50%	0.40	250
Counterfactual 11	525	2200	25	250	0	16,000	2.1	75%–85%	0.80	
Scenario 12	>800	≥0	≥0	≥0	0	≥24,000	1.2	<50%	0.40	250
Counterfactual 2	525	2200	25	250	0	16,000	2.1	75%–85%	0.80	
Scenario 13	>800	≥0	≥0	≥0	0	<24,000	1.3	<50%	0.40	250
Counterfactual 13	525	2200	25	250	0	16,000	2.1	75%–85%	0.80	

Note: Scenarios for rain-fed rice are also considered here. In case of no irrigation, efficiency is set to the lowest class. All values are reported in BDT/acre as in the original survey module. Conversion rate acre to hectare: 0.404686. Official exchange rate (BDT per USD, period average 2020) for Bangladesh: 84.87 BDT/USD (World Bank, 2022).

APPENDIX B

Decision experiment
Game Steps:

1. Introduce the intensification decision experiment for allocation of inputs for cultivation of PQR – Explain with the example one. Please note that you must enter the example to Surveybe.
2. Surveybe will automatically calculate the optimal inputs and the yield. Enter the modern PQR price from the randomly selected choice card (Q9 in previous section).
3. Surveybe will automatically calculate the profit and difference in net profit between farmer's cultivation and optimal cultivation. This difference will be used to calculate the payoff amount.
4. Implement the actual intensification experiment with the allocation of inputs.
5. Enter the input data into Surveybe. Enter the modern PQR price from selected choice card (Q9 previous section).
6. Surveybe will automatically calculate net profit and difference in profits. The scaled down amount shown in Surveybe needs to be paid to the farmers for his decision.
7. Stop the time record and enter it in the time taken into the Surveybe.
8. Hand over the payoff to the farmer.

Protocol:

Now we will be giving you 30,000 BDT(*BDT*) as voucher money to invest in different inputs to produce premium quality rice variety (modern varieties) or you may save full or some. Your actual payoff will depend on the decisions you make. You can get a payoff from 250 BDT to 600 BDT. If you decide to save the full amount, this means you don't produce the crop. You will get 300 BDT, but if you decide to produce you can earn up to 600 BDT. If your decisions are suboptimal, you may earn only 250 BDT. Please note that you can partly invest and partly save the voucher money we gave you. If you decide to cultivate using full or part of 30,000 BDT voucher money, please consider that you are cultivating for one acre of paddy (100 decimals). The options of spending money are on seeds, fertiliser, herbicides/weeding, pesticides, irrigation and any other costs. Your yield will depend on how you spend across these inputs.

Warning: overspending of money on any particular inputs may not give you high yield, but underspending will reduce the yield. Difference in profit is calculated with the optimal production and your choice, and will be used to calculate the payoff. To practise this, we will ask you to do one example before we go for actual experiment.

ENUMERATORS: Please note, to practise this, you will have to ask the farmer to do one example before the actual game is played. During this example, you enter the details which the farmer gives and then tell him/her the hypothetical pay off. You can show the optimal amount of any one input to explain to the farmer how his/her decisions has affected the final payoff. After that tell the farmer to re-think his/ her decisions and play the actual game.

Explain the example to the farmers like this: In the example, your yield is -------- whereas the optimal yield is ----------. You were using --------- input substantially higher/lower than required. Hope this will help you to improve your decision in the real experiment.

Example: How much to spend money (total 30,000 BDT) (*aman*) for 100 decimals (100 decimals equal 0.404648 ha).

Investment options	Farmer response	Optimal (automatic)
Healthy seeds (BDT)		
Fertiliser cost (BDT)		
Herbicides/Weeding (BDT)		
Pesticide (BDT)		
Irrigation (BDT)		
Other Cost		
Savings (don't spend)		
Yield (t/acre)		
Price (BDT per kg) (take the price of PQR from the selected choice card)		
Net profit (BDT per acre)		
Difference in net profit	**PQR farmer – PQR automatic**	

Now let play the actual game. Please note that we will use this profit to calculate your pay off.

Experiment: How much to spend money (total 30,000 BDT) (*aman*) for 100 decimals (100 decimals equal 0.404648 ha).

Investment options	Farmer response	Optimal (automatic)
Healthy seeds (BDT)		
Fertiliser cost (BDT)		
Herbicides/Weeding (BDT)		
Pesticide (BDT)		
Irrigation (BDT)		
Other Cost		
Savings (don't spend)		
Yield (t/acre)		
Price (BDT per kg) *(take the price of modern PQR from the selected choice card)*		
Net profit (BDT per acre)		
Difference in net profit	**PQR farmer – PQR automatic**	

If it is an incentivised experiment treatment,
Pay out to farmers -------- BDT(calculate automatically).
Enumerator has to take receipt, team lead pay the amount indicated and take a photo of handing over cash to farmer.

APPENDIX C

Treatments

C.1 | TREATMENT: CHEAP TALK
Step 1: Read out the cheap talk script and explain to farmers.

  Cheap Talk script

You will be soon asked to make a hypothetical choice on PQR involving money. Studies showed that people tend to act differently when there is no actual payment just like the one you are about to make. For example, in a recent study on flood tolerant rice variety, on average several people said they pay high for getting the seeds of this variety, but when we offered the product they paid lower than what they said they would pay for it.

Why do people behave differently? They might think that 'I really really want to buy improved seeds'. But when it comes to reality, we think a different way and there can be several reasons not to buy. It might be that it is too difficult to measure the impact or effect of a purchase of improved seeds. Another possibility is that it might be difficult to visualise getting the seeds from the seed dealers and paying a higher price for it. There might be some other household needs that they might not have considered while choosing in the hypothetical scenario.

We want you to think and behave in the same way that you would do if you really had to invest for PQR and produce in the next season. Please take into account how much you really want to produce, as opposed to other alternatives that you like or any other constraints that might make you change your behaviour, such as seed availability, agricultural budget etc. *Please accept the exact context you faced and accordingly try to really put yourself in a realistic situation while making the choice.*

  Step 2: Ask the farmers to summarise what they have learnt with the above script.

C.2 | TREATMENT: HONESTY PRIMING
In this session, we ask farmers to choose the closest meaning of the words listed below. Farmers can choose three closest ones among six synonyms provided against each word. Enumerator: please give an example word to farmer so that it is easy to understand.

  Step 1: Introduce the priming example to farmer.

  Example word: light.

  Please choose three closest meanings to the word from below: brightness, day, illumination, shining, run, glow.

  Step 2: Ask the farmers to pick the meanings that are very close to the word.

ID	Words	Synonyms
1	Shotyobadi	Shott, shadhu, probhat, bishwa, shatcharitra, okopot
2	Shotota	Meetha, shuddhata, neeti, bishuddhata, shadhuta, bhor
3	Shokal	Bhor, pratohkal, probhat, bhaya, shoishob, nojor
4	Shottyo	Nirbhul, drishti, jathartha, khati, nojor, ashol
5	Prithibi	Pratohkal, jogot, bishwa, dhora, bhumi, dhoop
6	Sposhtobadi	Okopot, modhur, shorol, shoja, bhumi, kholakhuli
7	Antorik	Chholonaheen, dost, kopototashunyo, okopot, antorikpurno, porijon
8	Khati	Dhoop, aashol, nikhad, okopot, bhanu, bishwashjogyo

C.3 | TREATMENT: NEUTRAL PRIMING
In this session, we ask farmers to choose the closest meaning of the words listed below. Farmers can choose three closest ones among six synonyms provided against each word. Enumerator: please give an example word to farmer so that it is easy to understand.

Step 1: Introduce the priming example to farmer.

Example word: light.

Please choose three closest meanings to the word from below: brightness, day, illumination, shining, run, glow.

Step 2: Ask the farmers to pick the meanings that are very close to the word.

ID	Words	Synonyms
1	Mishti	Mithai, mishtannya, bhor, madhur, meetha, jogot
2	Bondhu	Mitra, chakhhu, dhora, dost, porijon, bhaya
3	Prithibi	Pratohkal, jogot, bishwa, dhora, bhumi, dhoop
4	Shoorjo	Bhanu, robi, roudro, dhup, bhumi, modhur
5	Chokh	Chokhhu, bishwa, nojor, drishti, pobhat, noyon
6	Shokal	Bhor, pratohkal, probhat, bhaya, shoishob, nojor
7	Aakash	Gogon, aashman, nobho, ombor, dhoop, dhora
8	Chaand	Robi, chandra, bhaya, shoshi, chandrama, chanda

C.4 | PQR CHOICE EXPERIMENT

In this choice experiment we will ask you to choose between *three alternatives*.

1. *Traditional Premium Quality Rice (PQR)*, such as Kalijira or Khatari bhog etc., are the ones traditionally been cultivated and having aroma. They are low yielding, but fetch a very high price in the market.
2. *Modern PQR* – These are high yielding aromatic varieties developed by research institutions such as BRRI dhan 34 (chinigura), BRRI dhan 50 (Banglamoti) etc.
3. *Non-PQR* – These are non-aromatic varieties such as Swarna, BR28, BR 29 etc.

Type of variety	Aman	Boro
Traditional PQR	Kalijira/khatari bhog	–
Modern PQR	BRRI dhan34 (chinigura)	BRRI dhan50 (Banglamoti)
Non-PQR	Swarna	BR28/BR29

APPENDIX D

Main variables included in surveys and analysis

Variable name	Description
Dependent variables	
Efficiency (field data)	Efficiency scores calculated based on plot-level observations
Efficiency (hypothetical input allocation data)	Efficiency scores assigned based on RM survey data. To simplify calculation four efficiency categories for a wide range of different input combinations were designed
Rice yield (kg/ha)	Rice yield of plot per ha in kg. Yield will be logarithmised
Control variables (Household level)	
Age of household head (years)	Age of household head in years
Female headed household (=1)	Household is headed by female member (1=female household head; 0=otherwise)
Education of household head (years)	Years of education of household head
Muslim (=1)	Religion of household head (1=Muslim, 0=other)

Variable name	Description
Number of adults	Number of adult household members (older than 16 years)
Own cultivated land (ha)	Total farm size in ha, which includes all land owned by the household either formal or informal
Household consumption expenditure (log)	Annual consumption expenditures for food, health, and education (BDT) in log
Farming main occupation (=1)	Household head reports farming as primary occupation
Cognitive score	Count variable for number of correct answers. Maximum value is six
Access to credit (=1)	If any of the household members had taken a loan in the last 12 months (1 = yes, 0 = no)
Access to credit from bank (=1)	If any of the household members had taken a loan from a bank in the last 12 months (1 = yes, 0 = no)
Cultivated PQR in aman season (=1)	Household is cultivating any PQR variety (1 = yes, 0 = no)
Received PQR extension service (=1)	If any household member in the last 12 months received any advice about PQR varieties (1 = yes, 0 = no)
Intended share of rice land with PQR (0–100)	Percentage of farms' rice area that a farmer would hypothetically cultivate with any PQR variety (0–100)
Mobile phone ownership (=1)	Household head owns a mobile phone (1 = yes, 0 = no)
Smartphone ownership (=1)	Household owns a smartphone (1 = yes, 0 = no)
Member of any farm organisation (=1)	Household is member in Farmers' cooperative, Self-help group, Farmer clubs or Water/Irrigation committee (1 = yes, 0 = no)
Member of any non-farm organisation (=1)	Household is member in Union Porishod/Pouroshobha, Credit society/ cooperative bank, NGO, Political party, Women and child care committee, Forest management committee, Education Committee, or Others (1 = yes, 0 = no)
Share of PQR farmers in village (0–1)	Share of farmers that adopted PQR in village. The share ranges from 0 to 1 (0–1)
Pre COVID-19 (=1)	Household was interviewed before the COVID-19 pandemic (1 = yes, 0 = no)
Cheap talk (=1)	The enumerator read out a cheap talk script to the farmer (1 = yes, 0 = no)
Honesty priming (=1)	Farmers were asked to select three words out of list of six words that that were closest in meaning to one assigned word. This task was repeated eight times with different words. The provided word sets were related to honesty (1 = yes, 0 = no)
Neutral priming (=1)	Farmers were asked to select three words out of list of six words that that were closest in meaning to one assigned word. This task was repeated eight times with different words. The provided word sets were neutral in their meaning (1 = yes, 0 = no)
Max. attainable yield of rice (kg/ha)	Maximum attainable yield for rice (irrigated, intermediate input) cultivation at village level based on data from Global Agro-Ecological Zone (GAEZ) database
Control variables (Plot level)	
Seeds (USD/ha)	Input of seeds in monetary terms
Fertiliser investment (USD/ha)	Input of fertiliser in monetary terms
Herbicide/Weeding (USD/ha)	Input of weeding and herbicide application in monetary terms
Irrigation (USD/ha)	Input of irrigation in monetary terms
Pest control products (USD/ha)	Input of insecticides and fungicides (powder and spray) in monetary terms
Other costs (USD/ha)	Including all other potential costs in monetary terms such as harvesting and crop establishment

APPENDIX E

TABLE E1 Randomisation of treatments.

	(1)	(2)	(3)
	Cash incentive	**Cheap talk**	**Honesty Priming**
Age of household head	0.000	−0.000	0.001
	(0.001)	(0.001)	(0.001)
Education of household head (years)	0.004	0.001	−0.003
	(0.003)	(0.002)	(0.003)
Own cultivated land (decimal)	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)
Household consumption exp. (log)	0.033	−0.011	0.013
	(0.025)	(0.019)	(0.021)
Percentage of rice cultivation with PQR	−0.000	−0.001***	0.000
	(0.000)	(0.000)	(0.000)
Constant	1.041***	0.362	0.069
	(0.283)	(0.223)	(0.232)
F-statistic	1.127	3.378	0.712
R^2	0.003	0.011	0.002
Observations	1418	1418	1418

Note: OLS models used for all regressions. Standard errors clustered at village level in parentheses are reported.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE E2 Validation—hypothetical bias.

	Obs.	Efficiency score (mean)	Efficiency score (min)	Efficiency score (max)
Cash incentive				
No	793	0.537	0.400	0.900
Yes	627	0.534	0.400	0.900
Cheap talk				
No	1216	0.539	0.400	0.900
Yes	204	0.518*	0.400	0.900
Honesty priming				
No	1021	0.533	0.400	0.900
Yes	399	0.542	0.400	0.900

Note: A Mann–Whitney U test was used to determine statistically significant differences between the groups.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE E3 Validation of the hypothetical input allocation–likelihood of highest efficiency class.

	(1)	(2)
	Highest efficiency class (=1)	Highest efficiency class (=1)
Cash incentive (=1)	1.149	1.081
	(0.317)	(0.297)
Cheap talk (=1)	0.503	0.482
	(0.281)	(0.273)
Honesty priming (=1)	1.331	1.335
	(0.285)	(0.316)
Price of modern PQR (USD/kg)	0.249	0.424
	(0.259)	(0.497)
Cognitive score (1–6)	1.099	1.051
	(0.135)	(0.131)
Additional controls	No	Yes
Wald χ^2	8.309	94.852
Pseudo-R^2	0.014	0.131
N	1416	1054

Note: Logit models used for all regression. Additional controls include all control variables specified in Equation (2). Odds ratios with standard errors clustered at village level in parentheses are reported.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE E4 Validation of the hypothetical input allocation—training example.

	Survey data		Training example	
	Mean	Std. dev.	Mean	Std. dev.
Seeds (USD/ha)	31.913**	20.849	32.705	24.014
Fertiliser (USD/ha)	115.448***	59.569	112.717	59.328
Herbicides/weeding (USD/ha)	31.680	32.869	31.613	31.934
Pesticide (USD/ha)	93.391***	62.792	90.327	59.850
Irrigation (USD/ha)	47.673	41.443	47.752	41.944
Other costs (USD/ha)	373.264	107.713	370.169	132.131

Note: 1420 observations. A one-sample *t*-test was used to determine statistically significant differences.

**$p < 0.05$; ***$p < 0.01$.

TABLE E5 Determinants of allocative efficiency in the hypothetical input allocation.

	Ordered logit			
	(1)	(2)	(3)	(4)
	Full sample	Dinajpur district	Sherpur district	Jhenaidah district
Received PQR extension service (=1)	1.304*	1.617**	0.984	1.177
	(0.203)	(0.335)	(0.336)	(0.383)
Member of any farm organisation (=1)	1.427	1.150	1.309	3.422**
	(0.442)	(0.474)	(0.649)	(1.731)
Smartphone ownership (=1)	1.320**	1.177	1.442	1.635
	(0.174)	(0.207)	(0.466)	(0.490)
Mobile phone ownership (=1)	0.707	0.732	0.804	0.757
	(0.191)	(0.276)	(0.328)	(0.591)
Cultivated PQR in aman season (=1)	1.222	0.672	5.032***	1.006
	(0.304)	(0.194)	(2.430)	(0.515)
Age of household head	1.004	0.996	1.025*	0.998
	(0.005)	(0.006)	(0.013)	(0.011)
Female headed household (=1)	0.255	0.328		
	(0.424)	(0.555)		
Education of household head (years)	0.997	1.002	1.000	1.014
	(0.016)	(0.022)	(0.029)	(0.036)
Muslim household head (=1)	1.243	1.186	1.493	3.130**
	(0.355)	(0.363)	(0.567)	(1.466)
Number of adults	1.011	1.046	0.988	1.021
	(0.048)	(0.069)	(0.107)	(0.086)
Own cultivated land (ha)	1.000	1.000	0.999	1.001
	(0.000)	(0.000)	(0.001)	(0.001)
Farming main occupation (=1)	0.946	1.109	0.865	0.724
	(0.137)	(0.228)	(0.306)	(0.197)
Intended share of rice land with PQR (0–100)	1.005*	1.001	1.010	1.007
	(0.003)	(0.006)	(0.006)	(0.005)
Member of any non-farm organisation (=1)	0.815	0.946	0.475*	0.940
	(0.127)	(0.184)	(0.200)	(0.312)
Household consumption exp. (log)	0.746**	0.706*	1.031	0.578
	(0.107)	(0.132)	(0.334)	(0.197)
Cognitive score	1.216***	1.185**	1.161	1.133
	(0.075)	(0.082)	(0.162)	(0.216)
Share of PQR farmers in village (0–1)	0.575	0.183	1.072	0.276**
	(0.203)	(0.226)	(0.642)	(0.175)
Maximum attainable yield of rice (kg/ha)	0.994	0.998	0.996	0.912
	(0.004)	(0.006)	(0.008)	(0.071)
Constant				

(Continues)

TABLE E5 (Continued)

	Ordered logit			
	(1)	(2)	(3)	(4)
	Full sample	Dinajpur district	Sherpur district	Jhenaidah district
Sub-district fixed effects	Yes	Yes	Yes	Yes
Wald χ^2/F-statistic	118.637	86.134	170.483	90.113
Pseudo-R^2/R^2	0.055	0.064	0.086	0.081
Observations	1418	719	319	380

Note: PQR stands for premium quality rice. Ordered logit models used for columns 1–4. Odds ratios for columns 1–4. Standard errors clustered at village level are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE E6 Effect of PQR extension service on input allocation.

	(1)	(2)	(3)
	Seeds (USD/ha)	Irrigation (USD/ha)	Other costs (USD/ha)
Received PQR extension service (=1)	−2.163	0.174	13.431
	(1.506)	(2.395)	(9.010)
Age of household head	−0.062	−0.039	0.939***
	(0.044)	(0.070)	(0.244)
Female headed household (=1)	7.862	23.691	−111.279***
	(7.271)	(16.020)	(36.804)
Education of household head (years)	0.010	−0.115	1.023
	(0.132)	(0.213)	(0.788)
Muslim household head (=1)	−0.426	−2.654	−2.257
	(1.817)	(3.161)	(15.177)
Number of adults	−0.185	−2.125***	−6.794***
	(0.445)	(0.763)	(2.484)
Own cultivated land (ha)	−0.570	−2.960**	5.280
	(0.521)	(1.472)	(3.251)
Farming main occupation (=1)	1.012	−1.720	−21.295***
	(1.411)	(2.129)	(7.282)
Cultivated PQR in aman season (=1)	−2.354	−1.269	21.106
	(2.651)	(4.321)	(14.851)
Intended share of rice land with PQR (0–100)	0.005	−0.119	0.299
	(0.025)	(0.074)	(0.221)
Member of any farm organisation (=1)	−4.034	9.180	34.990*
	(3.000)	(7.095)	(18.434)
Member of any non-farm organisation (=1)	2.241	0.498	8.531
	(1.451)	(2.303)	(8.023)
Household consumption exp. (log)	2.607*	8.037***	16.456**
	(1.446)	(2.196)	(8.292)

TABLE E6   (Continued)

	(1)	(2)	(3)
	Seeds (USD/ha)	**Irrigation (USD/ha)**	**Other costs (USD/ha)**
Smartphone ownership (=1)	−1.008	−2.433	0.785
	(1.288)	(2.024)	(6.198)
Mobile phone ownership (=1)	3.783	−0.627	−7.900
	(2.789)	(3.021)	(15.561)
Cognitive score (1–6)	−0.784*	0.048	8.739***
	(0.469)	(0.970)	(3.012)
Share of PQR farmers in village (0–1)	0.959	7.788	−14.515
	(4.544)	(8.197)	(24.452)
Maximum attainable yield of rice (kg/ha)	−0.012	0.088	−0.202
	(0.032)	(0.059)	(0.258)
Constant	77.956	−567.522	1214.247
	(186.335)	(345.315)	(1505.847)
Sub-district fixed effects	Yes	Yes	Yes
F-statistic	3.814	14.346	5.595
R^2	0.131	0.425	0.198
Observations	1418	1418	1418

Note: PQR stands for premium quality rice. OLS models used for all regressions. Marginal effects with standard errors clustered at village level in parentheses are reported.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE E7   Input allocation in the hypothetical input allocation and versus counterfactual data.

	Input allocation data		Counterfactual data	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**
Seeds (USD/ha)	31.913	20.849	13.917	1.502
Fertiliser (USD/ha)	115.448	59.569	72.688	10.669
Herbicides/weeding (USD/ha)	31.680	32.869	3.304	3.870
Pesticide (USD/ha)	93.391	62.792	15.814	11.239
Irrigation (USD/ha)	47.673	41.443	6.011	9.658
Other costs (USD/ha)	373.264	107.713	409.580	59.173
Efficiency scores	0.536	0.176	0.842	0.049

Note: 1420 observations.

TABLE E8 Determinants of allocative efficiency and input use in the hypothetical input allocation (data from training example).

	(1)	(2)	(3)	(4)	(5)
	Ordered logit	OLS			
	Efficiency score	Efficiency score	Fertiliser (USD/ha)	Herbicide/weeding (USD/ha)	Pesticide (USD/ha)
Received PQR extension service (=1)	1.385**	0.024*	−8.225**	4.501	4.412
	(0.222)	(0.012)	(4.159)	(2.844)	(3.510)
Member of any farm organisation (=1)	1.754**	0.046	10.872	9.955	−9.473*
	(0.488)	(0.031)	(11.718)	(6.126)	(5.329)
Smartphone ownership (=1)	1.322**	0.021*	0.115	−5.380**	−5.149*
	(0.175)	(0.011)	(3.002)	(2.173)	(2.712)
Mobile phone ownership (=1)	0.866	−0.014	15.400***	3.819	7.106
	(0.268)	(0.025)	(5.541)	(3.259)	(4.543)
Cultivated PQR in *aman* season (=1)	1.136	0.009	−3.034	−4.580	6.033
	(0.304)	(0.023)	(6.460)	(5.270)	(5.162)
Age of household head	1.005	0.000	−0.088	0.090	−0.263**
	(0.006)	(0.000)	(0.122)	(0.070)	(0.121)
Female headed household (=1)	0.246***	−0.101***	17.867	13.342***	−19.415**
	(0.100)	(0.036)	(25.587)	(4.223)	(7.862)
Education of household head (years)	0.998	0.000	−0.709*	0.117	0.091
	(0.017)	(0.001)	(0.391)	(0.211)	(0.302)
Muslim household head (=1)	1.402	0.026	−0.203	6.097	2.909
	(0.431)	(0.021)	(4.653)	(3.882)	(4.962)
Number of adults	1.016	0.002	1.190	2.198***	0.997
	(0.055)	(0.004)	(1.284)	(0.728)	(0.958)
Own cultivated land (ha)	1.000	−0.000	−0.021**	−0.003	0.004
	(0.000)	(0.000)	(0.009)	(0.003)	(0.005)
Farming main occupation (=1)	0.981	−0.000	4.903	−2.617	5.922**
	(0.139)	(0.011)	(3.477)	(2.247)	(2.959)
Intended share of rice land with PQR (0–100)	1.001	0.000	−0.053	0.049	0.018
	(0.003)	(0.000)	(0.092)	(0.075)	(0.078)
Member of any non-farm organisation (=1)	0.878	−0.013	5.223	−1.231	−1.539
	(0.146)	(0.013)	(4.283)	(3.297)	(3.351)
Household consumption exp. (log)	0.799	−0.020	3.762	−5.439**	4.701
	(0.124)	(0.013)	(4.194)	(2.262)	(2.917)
Cognitive score	1.097	0.007	−1.155	−0.579	−0.975
	(0.066)	(0.005)	(1.481)	(1.003)	(1.376)
Share of PQR farmers in village (0–1)	0.652	−0.025	6.135	−14.457*	4.149
	(0.253)	(0.029)	(12.794)	(8.590)	(7.190)
Maximum attainable yield of rice (kg/ha)	0.987***	−0.001**	−0.132	0.034	0.057
	(0.005)	(0.000)	(0.148)	(0.139)	(0.073)

TABLE E8 (Continued)

	(1)	(2)	(3)	(4)	(5)
	Ordered logit	OLS			
	Efficiency score	Efficiency score	Fertiliser (USD/ha)	Herbicide/weeding (USD/ha)	Pesticide (USD/ha)
Constant		4.491***	821.220	−118.787	−268.835
		(1.628)	(860.104)	(806.291)	(427.318)
Wald χ^2/F-statistic	105.16	5.793	4.733	3.627	32.632
Pseudo-R^2/R^2	0.062	0.128	0.268	0.149	0.445
Observations	1418	1418	1418	1418	1418

Note: PQR stands for premium quality rice. Ordered logit models used for column 1, OLS for columns 2–5. Odds ratios for column 1 and marginal effects for column 2 are reported. Standard errors clustered at village level are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

APPENDIX F

Stochastic frontier using translog production function (ML estimates)

	Estimate	Std. error	z-value	Pr($>|z|$)
Fertiliser (log)	0.118	0.014	82.442	<2.2e-16***
Herbicide/wedding (log)	0.012	0.006	20.253	0.043**
Pesticide (log)	−0.002	0.0063	−0.409	0.683
Irrigation (log)	0.016	0.005	34.485	0.001***
Other costs (log)	0.572	0.026	219.009	<2.2e-16***
SigmaSq	0.166	0.012	136.883	<2.2e-16***
Gamma	0.101	0.073	13.773	0.168
Observations	782			
Log likelihood value	−380.352			
Mean efficiency	0.904			

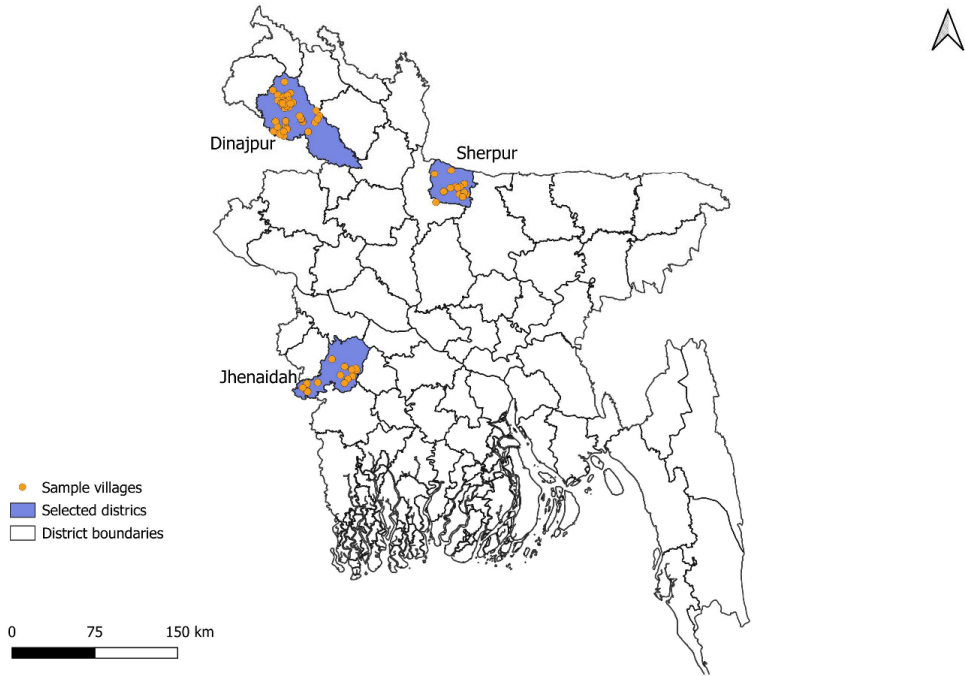*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

FIGURE F1   Map of selected districts and sample villages. The randomly selected sub-districts within each district are not shown in this map.