Economies of Scale and Heterogeneous Benefits of Improved Rice Varieties: Evidence from Smallholder Farmers in Cambodia - The Case Study in Bati District, Takeo Province, Cambodia

Viseth PRUM
Department of Agricultural and Resource Economics, Graduate School of Bioresource and Bioenvironmental Sciences, Kyushu University

NOMURA, Hisako
Laboratory of International Agricultural Development Studies, Department of Agricultural and Resource Economics, Faculty of Agriculture, Kyushu University

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Economies of Scale and Heterogeneous Benefits of Improved Rice Varieties Evidence from Smallholder Farmers in Cambodia
The case study in Bati district, Takeo province, Cambodia

Viseth PRUM[1,2] and Hisako NOMURA*

Laboratory of International Agricultural Development Studies,
Department of Agricultural and Resource Economics, Faculty of Agriculture, Kyushu University, Fukuoka 819–0395, Japan

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Adoption of improved rice varieties is widely promoted to enhance productivity and income, yet the magnitude of benefits may vary across farm structures and resource endowments. This study examines the heterogeneous impacts of adoption on rice yield and profit among smallholder farmers in Cambodia, focusing on economies of scale and complementary factors such as market access and asset ownership. Using the inverse probability weighted regression adjustment (IPWRA) method combined with individual interaction models, the analysis reveals that adopters experience significant gains—25.3% higher yield and 86.2% higher profit compared to non–adopters. Interaction results show that larger rice plots, better road conditions, and car ownership amplify adoption benefits, while remote locations and disease pressure also positively influence outcomes, suggesting adaptive management strategies. These findings underscore the importance of infrastructure, mobility, and technical support in maximizing the returns to improved rice technologies. Policy implications include targeted extension services, investment in rural roads, and promotion of collective farming models to leverage economies of scale.

Key words: improved rice varieties, economics of scale, heterogeneous, IPWRA, Cambodia

INTRODUCTION

The agricultural sector serves as a cornerstone of the Cambodian economy, with paddy rice cultivation being particularly central to livelihoods and national food security. Paddy rice in Cambodia is grown mainly under rainfed conditions, and the adoption of high–yielding rice varieties is generally limited. Constraints in policy promotion and technology dissemination have led to the low uptake of new technologies and the corresponding limitation in rice yield (FAO, 2010). The average rice yield in Cambodia in 2013 was 3.3 t/ha, the lowest among selected ASEAN countries. Vietnam led with an average paddy rice yield of 6.2 t/ha, followed by Indonesia (5.7 t/ha), Lao PDR (4.1 t/ha), and Thailand (3.5 t/ha), respectively (ADB, 2014). To boost rice production and enhance the net farm income of farmers, the Royal Government of Cambodia introduced a total of 10 high–yielding rice varieties. According to research conducted by CARD (2011), all 10 rice varieties yielded higher than traditional varieties, with the total average being 18 percent higher. The adoption of new agricultural technologies is often initially slow, as farmers are typically risk–averse when faced with uncertainties. However, as Feder and Umali (1993) note, observable positive outcomes from early adopters can significantly accelerate the rate of diffusion across a wider farming population.

The benefits of adopting improved rice varieties are hypothesized to be non–uniform and conditioned by farm size, plot fragmentation, market access, and resource endowments, reflecting economies of scale and complementary investments. A simple comparison between adopters and non–adopters without controlling for differences in characteristics can lead to biased estimations (Faltermeier and Abdulai, 2009). To address this issue, the inverse probability weighted regression adjustment (IPWRA) method is employed to control variations in farmers' characteristics. This study emphasizes two key concepts: economies of scale, where larger farm sizes and better resource endowments reduce per–unit costs and enhance returns, and heterogeneous benefits, indicating that adoption impacts vary across farmers depending on landholding, infrastructure, and asset ownership.

OBJECTIVE

This case study aims to examine the effects of adoption of the improved rice varieties on their economic well–being in Bati district, Takeo province, Cambodia.

MATERIALS AND METHODS

A two–stage sampling technique was employed in this study. The first stage involved purposive sampling, where two communes in the Bati district of Takeo province were selected. In the second stage, random sampling was conducted using a random integer generator website (https://www.random.org/integers/). Farmers cultivating any of the 10 high–yielding rice varieties were categorized as adopters, while those still cultivating tra-

[1] Department of Agricultural and Resource Economics, Graduate School of Bioresource and Bioenvironmental Sciences, Kyushu University, Japan
[2] Ministry of Agriculture, Forestry, and Fisheries (MAFF), Cambodia
* Corresponding author: H. Nomura (Email: hnomura@agr.kyushu–u.ac.jp)

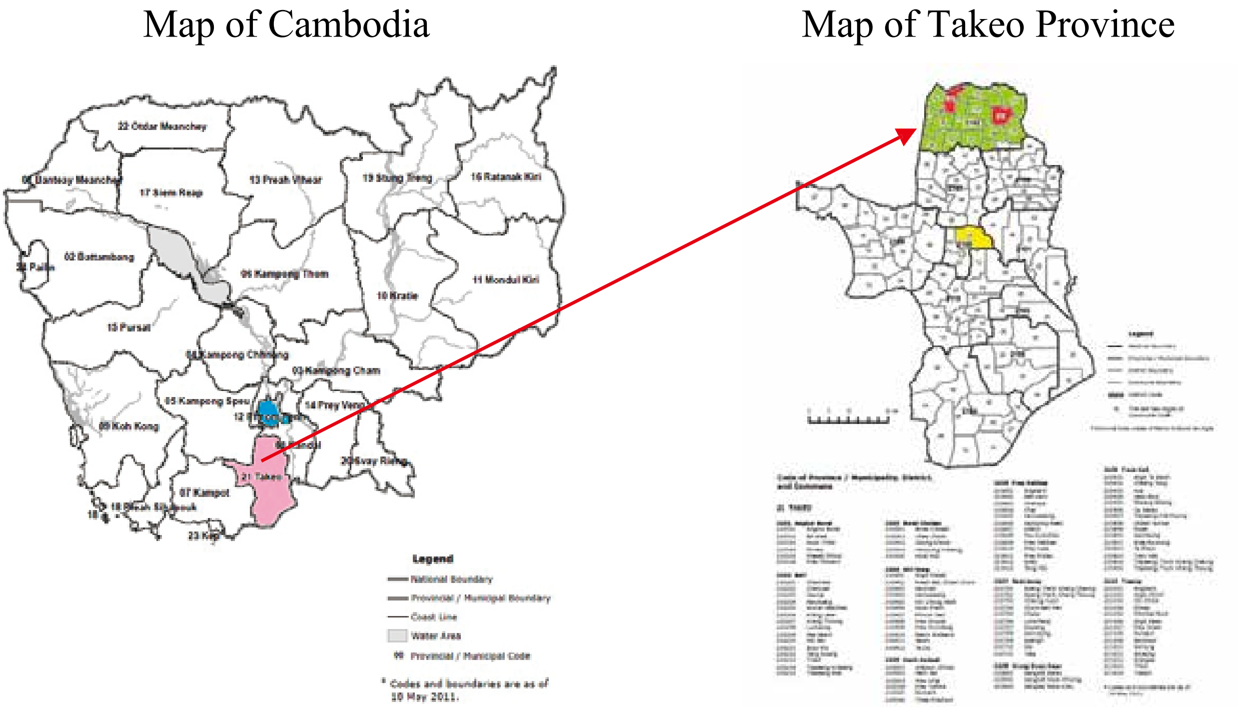

Fig. 1 Map of the study area

Source: National Institute of Statistics (NIS), 2013

ditional varieties were classified as non–adopters. Consequently, 151 adopter farmers and 151 non–adopter farmers, totaling 302 farmers, were selected as the respondent household sample. The field survey took place from late August to early October 2014, and semi–structured face–to–face interviews were conducted. In addition, the focus group discussed were conducted to get further insights related to their rice farming practices.

A farmer's decision to adopt new technology is often influenced by a combination of individual socio–economic characteristics and farm–specific factors. A straightforward comparison without accounting for these varying characteristics can lead to biased estimations. To accurately assess the effects of adopting new technology, it is essential to control for differences in characteristics between adopters and non–adopters. While propensity score matching (PSM) has been widely used, it has several limitations, including the discarding of unmatched observations, adjustment solely through the propensity score, and potential for bias due to model misspecification. Therefore, this study applies IPWRA, a doubly robust estimator that combines inverse probability weighting with outcome regression, retaining all observations and improving efficiency and reliability in estimating treatment effects. In practice, the IPWRA estimation proceeds in two main steps. The first step involves modeling the probability of adoption (treatment model) using covariates. The second step models the outcomes (yield, profit) conditional on covariates and adoption. IPWRA provides consistent estimates if either model is correctly specified, retains all observations, and adjusts for both selection and outcome heterogeneity (Bang & Robins, 2005; Glynn & Katz, 2010).

To ensure the validity of the IPWRA estimates, several diagnostic procedures were conducted for both the treatment and outcome models. First, the overlap assumption was verified by examining the distribution of predicted propensity scores for adopters and non–adopters, ensuring that no observations had probabilities close to zero or one. The stability of the inverse probability weights was assessed to detect extreme or influential weights that could bias the results. Covariate balance was then examined after weighting using standardized mean differences (SMDs). Following Ridgeway et al. (2017), an absolute SMD value below 0.1 was considered indicative of satisfactory balance between treatment groups.

Finally, robustness checks were performed by comparing the average treatment effects derived from IPWRA with those obtained from conventional estimators such as probability score and ordinary least squares (OLS). The consistency in the magnitude and direction of treatment effects across estimators confirmed the reliability of the IPWRA results. These diagnostic steps collectively indicate that the IPWRA estimator appropriately adjusted for selection bias and produced consistent estimates under the double robustness property, where unbiased inference can be achieved if either the treatment or outcome model is correctly specified (Bang & Robins, 2005; Glynn & Katz, 2010; Austin & Stuart, 2015).

In the first step, a probability model was estimated to determine the propensity scores of each farmer using logit model was defined as Eq. (1):

$$P(D_i = 1|X_i) = \Phi(X_{i\gamma}) \quad (1)$$

where D_i =1 if farmer i adopts improved rice varieties, 0 otherwise; X_i is a vector of observed covariates; $\Phi(\cdot)$ denotes the cumulative normal distribution function; γ is the vector of coefficients. Weights for treated and control groups are computed as Eq. (2):

$$w_i = \frac{D_i}{P(D_i = 1|X_i)} + \frac{(1\text{–}D_i)}{1\text{–}P(D_i = 1|D_i)} \quad (2)$$

The estimation of the average treatment effect on the treated (ATET) and the outcome equation is estimated as Eq. (3):

$$Y_i = \alpha + \beta D_i + \delta X_i + \varepsilon_i \quad (3)$$

The average treatment effect on the treatment treated (ATET) is computed as Eq. (4):

$$ATET = E[ln(Y_1) - ln(Y_0)|D = 1] \quad (4)$$

where $\ln(Y_1)$ = expected log of the aggregated weighted rice yield/profit for adopters,

$\ln(Y_0)$ = expected log of aggregated weighted rice yield/profit for non–adopters.

Second step, regression adjustment was conducted to assess the factors affecting yield and profit across different points of distribution, weighted by the inverse of their estimated probabilities is written as Eq. (5):

$$Y_i = X_i'\beta_q + \mu_{qi} \quad (5)$$

where; $(Y_i|X_i) = X_i'\beta_q$; and β_q represents the estimated coefficients of the explanatory variables.

Then calculate the potential outcomes and their difference (ATET).

RESULTS

Descriptive results

Table 1 presents the summary statistics of the basic profile of the respondent farmers and the results of t–tests indicating statistical differences between the two farmer groups. Several variables indicate that the adopter group has significantly lower values than the non–adopter group.

The non–adopter farmers leverage larger family sizes to engage in more off–farm jobs leading to increased income. The non–adopters, with significantly higher off–farm income, and a greater percentage of households owning a car, appear to be economically wealthier than the adopters in terms of their non–farm economic status. Additionally, the non–adopters own more paddy field plots than the adopters. This higher number of plots for rice cultivation may require more farming labor, making it challenging for the non–adopters to embrace labor–intensive new technology as their family members are significantly committed to off–farm activities.

Meanwhile, the variables for which the adopter group in Table 1 exhibited a significantly higher value than the non–adopter group are gender, paddy field size, distance to main roads, distance to the market, farm labor used, and family labor cost. The adopter farmers have significantly more males than the non–adopters, probably because this pertains to the more labor–intensive features of improved rice farming, such as land preparation and application of synthetic pesticides, than traditional rice farming. Additionally, the adopter farmers own a significantly larger paddy field than the non–

Table 1. Socio–economic and demographic profile of the respondent farmers

Variables	Unit	Adopters (n=151)		Non–adopters (n=151)		Difference	t–Test
		Mean	SD	Mean	SD		
Household size	No.person	4.54	1.43	5.03	1.68	–0.49***	2.73
Age	Years	47.95	12.84	47.09	12.61	0.86	0.59
Education	Years	5.17	3.08	5.00	3.43	0.17	0.46
Gender (1=male)	Dummy	0.83	0.38	0.70	0.46	0.13***	2.73
Paddy field size	Ha	0.99	0.64	0.81	0.52	0.19***	2.79
Number of rice plots	Number	1.66	0.83	2.35	1.42	–0.70***	5.19
Distance to paved roads	Km	4.85	2.29	3.64	1.99	1.22***	4.93
Distance to the market	Km	6.84	1.67	6.23	1.66	0.61***	3.18
Own cars	Dummy	0.02	0.14	0.09	0.29	–0.07***	2.77
Own motorbikes	Dummy	0.76	0.43	0.68	0.47	0.08	1.54
Cow amount	Number	1.27	1.34	1.68	1.41	–0.41***	2.30
Engage in off farm job	Dummy	0.14	0.35	0.70	0.46	–0.56***	11.83
Family labor cost	USD	177.78	5.88	136.97	5.60	40.81***	5.02
Farm labor used	Days	101.31	26.92	59.32	24.36	41.99***	14.21

Source: Own survey, 2014
*Note: p < 0.01***, p < 0.05**, p < 0.1**
Exchange rate: 1 USD was equivalent to 4,065 Riel (National Bank of Cambodia as of 1 September 2014)

adopter farmers. This is likely because improved rice varieties are more commercially oriented than traditional varieties in terms of market demand, and their benefits are better cultivated by growing them in a larger paddy field. The commercial orientation of the improved rice varieties is also evident in the higher farmgate price received by the adopters compared to the non–adopters. The adopter farmers have a longer distance to main roads and markets than the non–adopter farmers, probably because buyers tend to visit their rice farms to make purchases, while the non–adopter farmers must sell their rice themselves at the nearest market. Additionally, adopter farmers have significantly higher on number of labor days used as well as family labor cost meaning that they have spent time and effort on their rice farming. Education, age and asset motorbikes are not statistically significant.

Empirical Results

The results from the Inverse Probability Weighted Regression Adjustment (IPWRA) estimator are presented for rice yield in table 2 and rice profit in table 3.

The Result of IPWRA on Rice Yield

Table 2 presents the results of the IPWRA estimation, which indicate that adopters of improved rice varieties achieved significantly higher yields compared to non–adopters. The estimated Average Treatment Effect on the Treated (ATET) is 0.253 with a robust standard error of 0.060, and the effect is statistically significant at the 1% level ($p < 0.01$). This implies that, on average, adoption of improved rice varieties increases log yield by approximately 25.3%.

The model satisfies key assumptions, including overlap and convergence, confirming the robustness of the estimates. These findings are consistent with previous studies, such as Asfaw et al. (2012) and Becerril and Abdulai (2010), which also highlight the productivity gains associated with the adoption of improved agricultural technologies.

To validate the IPWRA estimates, a separate linear regression was conducted with rice yield as the dependent variable (Table 3). Moreover, to explore how the effect of adoption varies across household characteristics, a series of individual interaction regressions have been conducted. Each model included an interaction term between the treatment variable (d_adoption) and one covariate of interest, along with a consistent set of control variables. Dummy variables were specified using factor notation (i.) to ensure proper group comparisons, while continuous variables were interacted using (c.). This approach allowed us to isolate and interpret the moderating effect of each variable on the adoption outcome. In each regression focused on the interaction term (e.g., adopter#male for gender) to assess whether the effect of adoption differs across subgroups. The results are summarized in a main interaction table, which includes the coefficient, standard error, t–value, p–value, and confidence interval for each interaction term.

The table did not include model–level statistics (e.g., R–squared, F–statistic, Root MSE) in the table, as these vary across models and are not the focus of the interaction summary. However, all models were statistically significant overall, with R–squared values ranging from approximately 0.51 to 0.52.

For interpretation, the true effect of adoption for a subgroup is calculated as the sum of the main effect of adoption (d_adoption), and the interaction term for that subgroup. For example, in the gender interaction model that the effect of adoption for female households (reference group) is the coefficient of d_adoption (e.g., 0.3033) and the interaction effect is (0.1044889) so the true effect for male = 0.3033 + 0.1045 = 0.4078. This method was applied consistently across all interaction

Table 2. Average treatment effect of adopter and non–adopter for yield

Iteration 0: EE criterion = 1.931E–23

Iteration 1: EE criterion = 4.748E–32

Treatment–effects estimation Number of obs = 302

Estimator : IPW regression adjustment

Outcome model: linear

Treatment model: logit

log_yield	Coefficient	Robust std. err.	z	P>z	[95% conf.	interval]
ATET						
d_adoption						
(adopter vs non–adopter)	0.253***	0.060	4.24	0.000	0.136	0.370
POmean						
d_adoption						
non–adopter	7.803***	0.059	133.15	0.000	7.688	7.918

Source: Own survey, 2014

*Note: p < 0.01***, ATET: average treatment effect on treated; Paddy rice yield (t/ha)*

Table 3. Results of Regression for Rice Yield

log_yield	Coefficient	Robust std. err.	t	P>t	[95% conf.	interval]
d_adoption#gender						
adopter#male	0.408	0.017	0.24	0.812	–0.030	0.038
d_adoption#c.rice_plots						
adopter	0.421***	0.079	4.30	0.000	0.185	0.497
d_adoption# c.distance_tarred						
adopter	0.273***	0.033	–3.33	0.001	–0.174	–0.045
d_adoption#asset_car						
adopter#Yes	0.236**	0.018	2.07	0.039	0.002	0.071
d_adoption#d_off_income						
adopter#1	0.356	0.116	–0.38	0.704	–0.272	0.184
d_adoption#c.total_fam_day						
adopter	0.442	0.020	0.11	0.916	–0.037	0.041
d_adoption#extension						
adopter#Yes	0.414	0.066	0.35	0.730	–0.108	0.154
d_adoption#road_good						
adopter#Yes	0.337**	0.001	–2.41	0.017	–0.006	–0.001
d_adoption#disease						
adopter#Yes	0.434**	0.001	–2.41	0.017	–0.006	–0.001

Source: Own survey, 2014
*Note: $p < 0.01$***, $p < 0.05$***

models to ensure clarity and comparability.

The analysis indicates that rice yield is positively associated with rice yield and its interaction with key household and farm characteristics is shown in table 3. Farmers with more rice plots achieve higher yields (Coefficient = 0.421, $p < 0.001$), likely because more rice plots provide greater flexibility and better management opportunities for rice production. Longer distances to tarred roads are also linked to higher yields (Coefficient = 0.273, p = 0.001), possibly reflecting that remote areas often have more fertile soil and lower land prices, enabling better production potential. Car ownership is positively associated with yield gains (Coefficient = 0.236, p = 0.039), suggesting that mobility and access to inputs, as well as greater capital for rice investment, enhance productivity because who has is rich. Good road conditions further increase yields (Coefficient = 0.337, p = 0.017), likely by facilitating timely input delivery and field management. Interestingly, disease presence is also positively associated with higher yields (Coefficient = 0.434, p = 0.017), which may indicate that farmers facing disease pressure invest more effort and resources in crop care, following technical recommendations from agricultural experts, thereby improving overall performance and gain higher yield. Other factors, such as gender, off–farm income, total farm labor, and extension services, do not show significant associations with yield outcomes when interacting with adoption status.

Average treatment effect of adopter and non–adopter for profit

Table 4 presents the results of the IPWRA estimation for profit, showing that adopters of improved rice varieties earned significantly higher profits compared to non–adopters. The estimated Average Treatment Effect on the Treated (ATET) is 0.862, with a robust standard error of 0.097, and the effect is statistically significant at the 1% level ($p < 0.01$). This implies that, on average, adoption of improved rice varieties increases log profit by approximately 86.2%.

The model satisfies key assumptions, including overlap and convergence, as indicated by the extremely small EE criterion values, confirming the robustness of the estimates. These findings reinforce the economic benefits of adopting improved rice technologies and align with previous research highlighting the profitability of agricultural innovation.

The interaction analysis in table 5 reveals that rice profit is positively associated with adoption and its interaction with key household and farm characteristics, reflecting how these factors shape farmers' ability to capture market opportunities. Farmers with more rice plots achieve significantly higher profits (Coefficient = 0.922, $p < 0.001$), as larger landholdings provide greater flexibility in managing rice plantations and timing harvests to meet market demand with good price. Longer distances to tarred roads are also linked to higher profits (Coefficient = 0.380, p = 0.001), which may indicate that farmers in remote areas cultivate improved varieties demanded by the market in sufficient volumes, attracting buyers willing to travel and pay premium prices. Car ownership strongly enhances profitability (Coefficient = 1.361, p = 0.039), as it improves mobility and transportation capacity while signaling greater capital investment

Table 4. Average Treatment Effect on Treated for Profit

Iteration 0: EE criterion = 4.595e–17

Iteration 1: EE criterion = 1.653e–30

Treatment–effects estimation Number of obs = 302

Estimator : IPW regression adjustment

Outcome model: linear

Treatment model: logit

log_profit	Coefficient	Robust std. err.	z	P>z	[95% conf.	interval]
ATET						
d_adoption						
(adopter vs non–adopter)	0.862***	0.097	8.86	0.000	0.671	1.053
POmean						
d_adoption						
non–adopter	5.377***	0.092	58.24	0.000	5.196	5.558

Source: Own survey, 2014
*Note: $p < 0.01$***, ATET: average treatment effect on treated; Paddy rice profit (USD/ha)*

in rice production. Good road conditions further increase profits (Coefficient = 0.643, p = 0.017), saving time and facilitating efficient business operations, including timely input delivery and easier transport of harvests. Interestingly, disease presence is also positively associated with profit (Coefficient = 1.048, p = 0.017), suggesting that farmers under disease pressure invest more attention and resources in crop care, often following technical recommendations from agricultural experts and meet the market requirement with good price, which ultimately improve returns. Other factors, such as gender, off–farm income, family labor costs, and extension services, do not show significant associations with profit outcomes when interacting with adoption status.

DISCUSSION

The IPWRA results provide robust evidence that the adoption of improved rice varieties significantly enhances both rice yield and profit. Specifically, adopters experienced a 25.3% increase in log yield and an 86.2% increase in log profit compared to non–adopters, with both effects statistically significant at the 1% level. These findings confirm the productivity and economic benefits of improved rice technologies and align with previous studies such as Asfaw et al. (2010, 2012) and Becerril and Abdulai (2010). The use of the doubly robust IPWRA estimator (Bang & Robins, 2005; Glynn & Katz, 2010) strengthens the reliability of these results by addressing potential selection bias and model misspecification.

To validate these estimates and explore heterogeneity in adoption benefits, separate linear regressions were conducted using individual interaction models. Each regression included an interaction term between adoption status and one household or farm characteristic, along with a consistent set of controls. This approach allowed us to isolate and interpret how adoption effects vary across subgroups.

Rice Yield

The analysis indicates that rice yield is positively associated with adoption and its interaction with key household and farm characteristics (Table 3). Farmers with more rice plots achieve significantly higher yields (Coefficient = 0.421, p < 0.001), likely because multiple plots provide greater flexibility in managing rice plantations and timing harvests to optimize production. Longer distances to tarred roads are also linked to higher yields (Coefficient = 0.273, p = 0.001), possibly reflecting that remote areas often have more fertile soil and lower land prices, enabling better production potential. Car ownership is positively associated with yield gains (Coefficient = 0.236, p = 0.039), suggesting that mobility and access to inputs, as well as greater capital for rice investment, enhance productivity. Good road conditions further increase yields (Coefficient = 0.337, p = 0.017), likely by saving time and facilitating efficient operations, including timely input delivery and easier transport of harvests. Interestingly, disease presence is also positively associated with higher yields (Coefficient = 0.434, p = 0.017), which may indicate that farmers facing disease pressure invest more attention and resources in crop care, often following technical recommendations from agricultural experts. Other factors, such as gender, off–farm income, total farm labor, and extension services, do not show significant associations with yield outcomes when interacting with adoption status. These findings are consistent with previous research highlighting the heterogeneous impacts of agricultural technology adoption shaped by farm structure and resource endowments (Marenya & Barrett, 2007; Doss, 2006; Khonje et al., 2015).

Table 5. Results of Regression for Rice Profit

log_profit	Coefficient	Robust std. err.	t	P>t	[95% conf.	interval]
d_adoption#gender						
adopter#male	0.941	0.017	0.24	0.812	–0.030	0.038
d_adoption#c.rice_plots						
adopter	0.922***	0.079	4.30	0.000	0.185	0.497
d_adoption# c.distance_tarred						
adopter	0.380***	0.033	–3.33	0.001	–0.174	–0.045
d_adoption#asset_car						
adopter#Yes	1.361**	0.018	2.07	0.039	0.002	0.071
d_adoption#d_off_income						
adopter#1	0.629	0.116	–0.38	0.704	–0.272	0.184
d_adoption# c.Family_cost_USD						
adopter	1.316	0.020	0.11	0.916	–0.037	0.041
d_adoption#extension						
adopter#Yes	1.375	0.066	0.35	0.730	–0.108	0.154
d_adoption#road_good						
adopter#Yes	0.643**	0.001	–2.41	0.017	–0.006	–0.001
d_adoption#disease						
adopter#Yes	1.048**	0.001	–2.41	0.017	–0.006	–0.001

Source: Own survey, 2014
*Note: $p < 0.01$***, $p < 0.05$***

Rice Profit

Similarly, the interaction analysis for rice profit (Table 5) reveals that profitability is positively associated with adoption and its interaction with key household and farm characteristics, reflecting how these factors shape farmers' ability to capture market opportunities. Farmers with more rice plots achieve significantly higher profits (Coefficient = 0.922, $p < 0.001$), as larger landholdings provide greater flexibility in managing rice plantations and timing harvests to meet market demand when prices are favorable. Longer distances to tarred roads are also linked to higher profits (Coefficient = 0.380, $p = 0.001$), which may indicate that farmers in remote areas cultivate improved varieties demanded by the market in sufficient volumes, attracting buyers willing to travel and pay premium prices. Car ownership strongly enhances profitability (Coefficient = 1.361, $p = 0.039$), as it improves mobility and transportation capacity while signaling greater capital investment in rice production. Good road conditions further increase profits (Coefficient = 0.643, $p = 0.017$), saving time and facilitating efficient business operations, including timely input delivery and easier transport of harvests. Interestingly, disease presence is also positively associated with profit (Coefficient = 1.048, $p = 0.017$), suggesting that farmers under disease pressure invest more attention and resources in crop care, often following technical recommendations from agricultural experts, which ultimately improve returns. Other factors, such as gender, off–farm income, family labor costs, and extension services, do not show significant associations with profit outcomes when interacting with adoption status.

These findings also reflect the theory of economies of scale, where larger farm sizes and better resource endowments reduce per–unit costs and enable farmers to achieve higher returns from improved technologies. The positive effect of rice plots and car ownership suggests that farmers with greater capacity can spread fixed costs over larger outputs, improving efficiency and profitability.

These findings underscore the heterogeneous nature of adoption benefits, shaped by farm structure, resource endowments, and market access. The positive association of rice plots, road conditions, and asset ownership with both yield and profit suggests that physical and financial capital play a critical role in maximizing the returns to improved technologies. The unexpected positive association of disease presence with outcomes may reflect adaptive management strategies and increased attention to crop care under stress conditions. Overall, these results highlight the importance of complementary investments in infrastructure, mobility, and technical support to fully realize the benefits of improved rice varieties. They also align with previous studies emphasizing that technology adoption interacts with household characteristics to influence productivity and profitability (Asfaw et al., 2010; Becerril & Abdulai, 2010; Marenya & Barrett, 2007; Khonje et al., 2015).

CONCLUSION

This study provides strong empirical evidence that the adoption of improved rice varieties significantly enhances both yield and profit among smallholder farmers in Cambodia. Using the IPWRA method, adopters experienced a 25.3% increase in log yield and an 86.2% increase in log profit compared to non–adopters, with both effects statistically significant at the 1% level. These findings confirm the productivity and economic benefits of improved rice technologies and highlight that these benefits are heterogeneous, shaped by economies of scale and complementary factors such as infrastructure and asset ownership.

To validate these results and explore heterogeneity, individual interaction regressions were conducted. For rice yield, adopters with more rice plots achieved higher yields, likely due to better management flexibility and timing of harvests. Longer distances to tarred roads were associated with higher yields, possibly reflecting better agroecological conditions and lower land costs in remote areas. Car ownership and good road conditions also amplified yield gains, highlighting the role of mobility and infrastructure. Interestingly, disease presence was positively associated with yield, suggesting that farmers under stress invest more attention and resources in crop care, often following technical recommendations.

For rice profit, similar patterns emerged. Larger rice plots were linked to higher profits, as they allow farmers to meet market demand with sufficient volume and capture favorable prices. Remote farmers cultivating improved varieties also benefited, as buyers are willing to travel for bulk purchases. Car ownership strongly enhanced profitability through improved transportation and capital investment, while good road conditions facilitated timely input delivery and efficient business operations. Disease presence again showed a positive association, indicating adaptive management and compliance with technical advice to maintain quality and marketability.

Across both models, socio–demographic factors such as age, gender, and education were not significant, suggesting that structural and resource–related factors matter more than personal characteristics in determining adoption benefits. Overall, these findings underscore the transformative potential of improved rice varieties in boosting productivity and income, while highlighting the importance of complementary investments in infrastructure, mobility, and technical support to fully realize these benefits.

POLICY IMPLICAITONS

The findings underscore the substantial benefits of adopting improved rice varieties in enhancing both yield and profit, but also reveal that these benefits vary across farm structures and resource endowments. Policies should leverage economies of scale by promoting land consolidation, collective farming models, and targeted support for farmers with larger plots. Infrastructure investments in rural roads and transport services are critical to amplify adoption benefits, while credit programs for productive assets can enhance mobility and market access. Extension services should focus on adaptive management strategies for disease control and provide inclusive training to ensure equitable benefits across households.

First, the positive association between rice plots and profitability suggests that policies should support farmers in optimizing land use and management. Extension programs can provide guidance on crop planning, staggered planting, and harvest timing to meet market demand and capture favorable prices. The Royal Government of Cambodia's policy of deploying extension officers in all agricultural communes remains critical. These officers, embedded within communities, can deliver technical advice, facilitate market linkages, and strengthen farmer capacity to manage multiple plots efficiently.

Second, the results highlight the importance of infrastructure and mobility. Good road conditions and car ownership significantly amplify adoption benefits, indicating that investments in rural roads, bridges, and transport services are essential to reduce transaction costs and improve access to inputs and markets. Complementary programs such as rural credit schemes for productive assets (e.g., vehicles, mechanization) can further enhance farmers' ability to commercialize rice production.

Third, the positive association of remote locations with higher profits suggests that market integration strategies should target these areas. Policies promoting aggregation centers, storage facilities, and buyer–farmer contracts can ensure that farmers producing improved varieties in remote regions can reliably access markets and negotiate better prices.

Fourth, the unexpected positive effect of disease presence on yield and profit indicates that farmers respond to crop stress by investing more in management and technical compliance. This underscores the need for robust extension services and timely dissemination of integrated pest and disease management practices. Strengthening farmer training and access to quality inputs will help sustain productivity under biotic stress.

Finally, inclusive support mechanisms remain vital. While socio–demographic factors such as gender and education were not significant in this study, extension programs should still ensure equitable access for female–headed households and resource–poor farmers. Promoting Modern Agricultural Cooperatives (MACs) can facilitate collective action, reduce input costs, and improve bargaining power, enabling smallholders to benefit more fully from improved rice technologies.

In summary, a combination of targeted extension services, infrastructure development, asset–based support, and market integration strategies is essential to maximize the impact of improved rice varieties and ensure equitable benefits across farming households.

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AUTHOR CONTRIBUTIONS

Viseth Prum: Conducted policy analysis and formulated policy implications based on empirical findings. Led the contextual interpretation of the case study on improved rice varieties introduced by the Cambodian government, highlighting the gap between expected outcomes and actual adoption rates. Provided insights into the low adoption despite the lack of official statistics, inferred by export volumes falling short of national targets.

Hisako Nomura: Provided strategic guidance and teaching throughout the research process. Supported the application of new analytical methods to an existing dataset, supervised data analysis and empirical modeling, and contributed to the interpretation of results. Offered critical input on manuscript development and policy implications, ensuring methodological rigor and practical relevance.

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