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Chapter 2
Impact of High-Quality Rice Variety on Profit and Profit Efficiency: Evidence from Vietnam

Phuc Trong HO

Abstract: High-quality rice varieties (HQRV) are expected to contribute more profit than conventional rice varieties. However, the observed profit gap is not attractive. This study assesses the impact of HQRV adoption on farmer profit and profit efficiency (PE) using farm-level data from 356 rice farmers surveyed in Vietnam's Mekong River Delta. We combine a propensity score matching (PSM) method and a stochastic profit frontier framework to mitigate the effects of selection biases and technology gaps. We use the PSM method to find a comparable non-adopter group to control selection bias associated with observed variables. A sample selection stochastic frontier model is then used to correct selection bias stemming from unobserved factors. Finally, we apply a stochastic meta-frontier approach to compare PE between groups. The analysis shows that the profit and PE gaps between the two groups are significantly underestimated if selection biases and technology gaps are not considered. A comparison of profit and PE scores reveals that HQRV adopters, on average, exhibit higher variable profits than non-adopters (1,085 USD/ha vs. 982 USD/ha) but lower PE performance (0.61 vs. 0.72), suggesting that adopters will benefit more from HQRVs if inefficiencies are eliminated. The results also indicate that farm size, contract farming, rice plots, and geographical and seasonal factors influence HQRV adoption.

1. Background

Vietnam has been one of the world's leading rice producers (with nearly 44 million tons) and exporters (nearly 6.1 million tons) for the last decade (GSO 2018). The Mekong River Delta is the main rice-intensified area for export, accounting for approximately 90% of the total export volume (accounting for 5.4 million tons of milled rice) (GSO 2018) (Figure 2.1). The observed profitability of rice farming remains low. One of the main reasons is that rice farmers still use the traditional low-quality rice varieties. To improve its output quality and price, the Vietnamese government introduced and encouraged farmers to adopt high-quality rice varieties and hopefully increase output prices, competitiveness advantage, and farmers' income. High-quality rice varieties (HQRVs) are expected to increase profits for rice farmers by 30%; however, the profit gap between these varieties and conventional ones is not as high as expected. The goal of this study is to analyze and address how much difference in the profit and profit efficiency is between HQRV adoption and non-adoption.

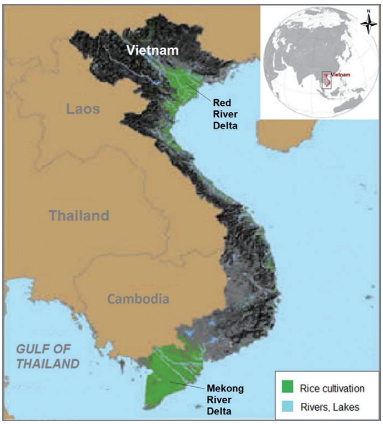

Figure 2.1 Distribution of rice area in Vietnam.
Source: (Shean 2012)

2. Research Approach

A direct comparison of profit and profit efficiency is not accurate due to (1) facing sample selection bias arising from both observable (e.g., age, education, and gender) and unobservable (e.g., risk preferences, motivation, and managerial ability) factors and (2) facing a technology gap between rice variety groups. Hence, to control sample selection bias and the technology gap between the two rice variety groups, this study uses a combined framework as applied in Villano et al. (2015). This is a combination of an impact evaluation technique (i.e., propensity score matching) and stochastic profit frontier framework to eliminate the potential effects of self-selection biases.

Step 1. A propensity score matching method (PSM) (Rosenbaum and Rubin 1983) is applied to correct selection bias stemming from observable variables.

Step 2. A sample selection corrected stochastic frontier model (Greene 2010) is employed to eliminate selection bias arising from unobservable factors.

Step 3. A stochastic meta-frontier approach (Huang et al. 2014) is applied to control the effects of the technology gap and make a direct comparison of profit efficiency between the two groups.

3. Empirical Models

(1) Propensity Score Matching (PSM)

The PSM method is implemented to identify comparable adopter and non-adopter groups using a propensity score or probability model (Logit or Probit). Here, the Probit model is applied to estimate propensity scores, which are then used to match adopters and non-adopters for farms falling within a common probability range (or common support). We tested several matching criteria (e.g., one-to-one, nearest neighbor, radius, kernel, and local linear regression matching), and the nearest neighbor matching is used because it generates a better-matched sample. In our case, we used five matches per adopter, with a caliper of 0.005.

The Probit model for matching is expressed as:

$$DHQR_i = 1[\sum_{n=1}^{i} \alpha_n z_{ni} + e_i > 0] \quad (1)$$

where i denotes farm, *DHQR* is a binary variable, 1 for adopters and 0 for non-adopters. Z_n is a vector of explanatory variables for farmers' adoption decisions, including farm and farmers' characteristics. α is the vector of unknown parameters to be estimated, and e is the disturbance term distributed as N (0,1)

(2) Sample Selection Stochastic Frontier (SF) Model

After obtaining a matched sample, matched subsamples can be used to estimate a stochastic profit frontier model for each group and compare the results. However, the decisions on HQRV adoption can be affected by unobserved factors (e.g., managerial ability), which could lead to differences in efficiency. Thus, the sample selection stochastic frontier model proposed by Green (2010) is used to mitigate the potential effects of self-selection bias from unobserved factors.

The sample selection (Probit) model is described as follows:

$$d_i = 1[\alpha' Z_i + w_i > 0],\ w_i \sim (0,1)$$

where d is a binary variable equal to 1 for adopters and 0 for non-adopters, Z is a vector of observed explanatory variables, and w is the unobservable error term.

Stochastic profit frontier model:

$$\pi_i = f\ (\beta;\ P_i;\ F_i)\ e^{(v_i - u_i)} \tag{2}$$

(π_i, P_i, Z_i) are observed only when $d_i = 1$ or $d_i = 0$, but not both

Composed error structure: $v_i - u_i$

Inefficiency term: $u_i \sim N^+(0,\ \sigma_u^2)$

Symmetric noise term: $v_i \sim N\ (0,\ \sigma_v^2)$

Error correlation between SF and selection model:

$$(w_i,\ v_i) \sim N_2\ [(0,0),\ (1,\ \rho\sigma_v,\ \sigma_v^2)]$$

where π_i is variable profit (equal to revenue less variable cost), P_i is a vector of input prices, F_i is a vector of fixed inputs, and the composed error term comprises the statistical noise term v_i and non-negative inefficiency term u_i. α and β are unknown parameters to be estimated. ρ shows the relationship between unobservable error in the sample selection model and statistical noise in the SF model.

However, PE between adopter and non-adopter groups cannot be directly compared because efficiency scores are estimated relative to each group's frontier, not relative to the meta-frontier and existing potential technology gaps between farmers using the two rice variety groups. Therefore, it is necessary to use a meta-frontier approach to generate a common frontier and estimate the technology gap ratio, which can construct a measure of overall PE.

(3) Stochastic Meta-Frontier Model

In Step 1, the SF model for each group is estimated:

$$\ln \pi_{ji} = \ln f^j(\beta_j;\ P_{ji};\ Z_{ji}) + v_{ji} - u_{ji} \tag{3}$$

Then, the profit efficiency scores are estimated, PE^j:

$$\widehat{PE_i^J} = \hat{E}\left(e^{-u_{jit}} \middle| (\widehat{v_{ji}} - \widehat{u_{ji}})\right)$$

In Step 2, the predicted values for adopters and non-adopters $\widehat{lnf^{J}}$ = (β_j; P_{ji}; Z_{ji}) are used as the dependent variables in the meta-frontier estimation:

$$\widehat{lnf^{J}}\,(\beta_j;\, P_{ji};\, Z_{ji}) = \ln f^{m}(\beta_j;\, P_{ji};\, Z_{ji}) + v_{ji}^{m} + u_{ji}^{m} \qquad (4)$$

Next, the technology gap is calculated, $\widehat{TGR_{\iota}^{J}} = \hat{E}\left(e^{-u_{ji}^{m}}\middle|(\widehat{v_{j\iota}^{m}} - \widehat{u_{j\iota}^{m}})\right)$

Then, it is possible to calculate meta-profit efficiency (Figure 2.2)

$$\widehat{MPE_{\iota}^{J}} = \widehat{TGR_{\iota}^{J}} \times \widehat{PE_{\iota}^{J}} \qquad (5)$$

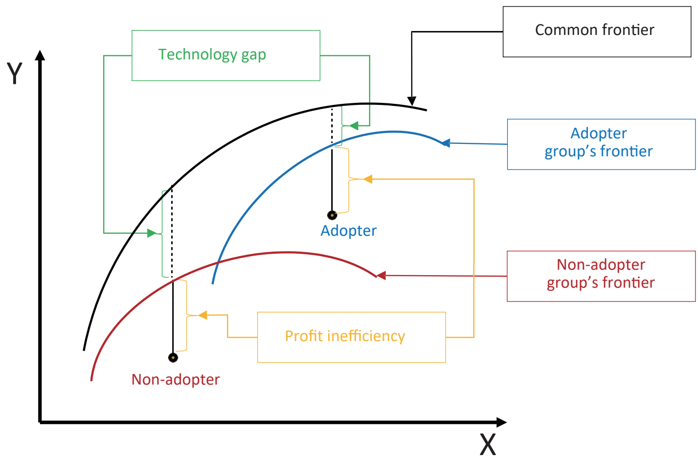

Figure 2.2 Meta-frontier approach.
Source: (Huang et al. 2014)

4. Data and Materials

This study was conducted in the Mekong River Delta. The sampling method is a three-step stratified random sampling technique. The sample size of 356 rice farmers was collected from 16 villages in three provinces: An Giang (AG), Can Tho (CT), and Bac Lieu (BL) (Figure

2.3), covering three cropping seasons of the production year 2016/2017. It generated 957 observations, with 414 adopters and 543 non-adopters. After matching, the remaining sample is 841 observations, with 319 adopters and 522 non-adopters.

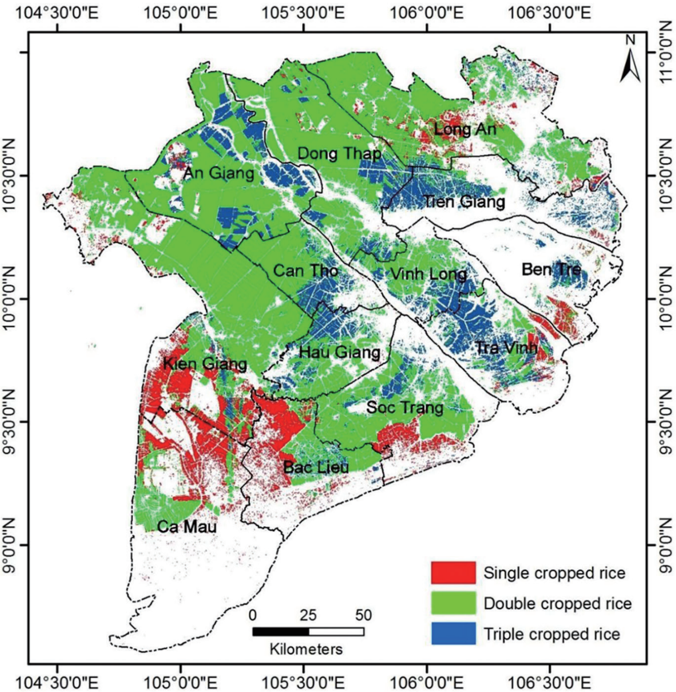

Figure 2.3 Rice Crop Map of the Mekong River Delta.
Source: (Nguyen et al. 2015)

As described earlier, the PSM method is used to identify a comparable control group to overcome the bias arising from differences in observed factors between groups. In this study, the observed variables included age (years), education (years of formal schooling), experience (years of rice farming), gender (1 for males, 0 otherwise), farm size (hectares), rice plots (numbers), and contract farming (1 for contract farming, 0 otherwise). Furthermore, two dummy variables of regions (Region 1-AG and Region 2-CT) and crop seasons (Season 2 and Season 3) are included to capture the effects of geographical settings and the effects of seasonal factors. These observed variables are regressed in the Probit model for the matching process and sample selection SF model.

5. Results

The result from Table 2.1 shows the influencing factors on decision-making on HQRV adoption or non-adoption based on the estimations of Probit selection models for HQRV using a full and matched dataset. It can be clearly seen that farm size and contract farming have positive effects on the farmers' decisions to become adopters, while the number of rice plots, regions, and seasons have negative effects on their decisions.

Table 2.1 Estimates of the Probit model for matching and sample selection model.

Variable	Full sample		Matched sample	
	Coef.†	S.E.	Coef.†	S.E.
Constant	1.240***	0.419	0.969**	0.437
Age	0.006	0.009	0.008	0.009
Education	-0.011	0.015	-0.023	0.016
Experience	-0.002	0.008	-0.004	0.009
Gender	0.188	0.251	0.230	0.267
Farm size	0.068*	0.027	0.072**	0.031
Rice plots	-0.138***	0.036	-0.156***	0.041
Contract farming	0.631***	0.176	0.616***	0.189
Region 1 (AG)	-1.879***	0.148	-1.558***	0.159
Region 2 (CT)	-1.783***	0.148	-1.497***	0.158
Season 2	-0.345***	0.108	-0.428***	0.113
Season 3	-0.498***	0.116	-0.529***	0.120
Model properties				
Log-likelihood (log*L*)	-485.88		-455.33	
X^2	337.49***		205.73***	

Pseudo R^2	0.258	0.184
Observations	957	841

Note: ***, **, * represent significant levels at 1%, 5%, 10%, respectively.

Source: Author

The result from Table 2.2 shows the comparisons in profit efficiency estimation between conventional SF models and sample selection SF models to select the best-fit model. Firstly, the pooled model is estimated using a log-likelihood ratio test to check whether only pooled model or separate estimation models are necessary. The result shows that it is necessary to estimate adopters and non-adopters separately. Also, the evidence on self-selection bias from unobservable factors and the log log-likelihood ratio test also show that it is necessary to additionally run a sample selection SF model.

Table 2.2 Estimates of conventional and sample selection SF models using matched sample data.

Variable	Conventional SF model						Sample selection SF model			
	Pooled		Adopter		Non-adopter		Adopter		Non-adopter	
	Coef.†	S.E.	Coef.†	S.E.	Coef.†	S.E.	Coef.†	S.E.	Coef.†	S.E.
Constant	9.596***	0.359	9.741***	0.663	9.905***	0.430	10.222***	0.767	9.931***	0.496
lnPseed	-0.084**	0.034	-0.126*	0.066	-0.017	0.043	-0.120	0.072	-0.020	0.054
lnPfertilizer	-0.364***	0.071	-0.398***	0.118	-0.328***	0.083	-0.257**	0.106	-0.338***	0.095
lnPlabor	-0.162***	0.037	-0.230***	0.081	-0.170***	0.040	-0.279***	0.092	-0.170***	0.046
lnLand	1.003***	0.051	0.970***	0.091	1.081***	0.062	1.041***	0.099	1.088***	0.076
lnCaptal	0.022	0.049	0.048	0.086	-0.049	0.062	-0.034	0.096	-0.056	0.075
Season 2	-0.267***	0.023	-0.335***	0.040	-0.204***	0.027	-0.381***	0.046	-0.195***	0.040
Season 3	-0.279***	0.025	-0.359***	0.045	-0.216***	0.026	-0.430***	0.052	-0.206***	0.040
HQRV	-0.040*	0.021	–		–		–		–	
Model properties										
Lambda (λ)	5.514***	0.021	6.905***	0.039	4.277***	0.024	4.654	–	4.264	–
Sigma_u	0.555***	0.017	0.677***	0.032	0.445***	0.018	0.665***	0.016	0.446***	0.010
Sigma_v	0.101***	0.009	0.098***	0.016	0.104***	0.010	0.143***	0.028	0.105***	0.010
Rho(w,v)	–		–		–		0.975***	0.142	0.262	0.500
Probot log*L*	–		–		–		-252.60		-202.72	

SF log*L*	-227.43	-140.00	-49.43	-136.13	-49.13
Total log*L*	-227.43	-140.00	-49.43	-388.74	-251.86
LR test	76.01***			7.74***	0.59
Observations	841	319	522	319	522

Note: ***, **, * represent significant levels at 1%, 5%, 10%, respectively.

Source: Author

As expected, all estimates for input prices are negative and significant, except for the seed price coefficient in the non-adopter models. The estimate for the land variable is positive and significant, while the estimate for the capital variable is not. The coefficients for the two-season dummies are negative and significant in all models, implying that variable profit tends to be lower outside the main growing season. The coefficient for the dummy variable of HQRV in the pooled models is negative and significant, implying that HQRV adopters exhibit lower profits than non-adopters.

Then, the stochastic meta-frontier model is run to calculate the technology gap ratio (Table 2.3). As expected, all coefficients for input prices, fixed cost, and season dummy variables are significant at the 1% level and consistent across models. The parameter estimates of sigma_u and lambda differ significantly from zero at the 1% level, capturing statistical evidence for the technology gap between the two groups.

Table 2.3 Estimates of stochastic meta-frontier model.

Variable	Full sample		Matched sample	
	Coef.[†]	S.E.	Coef.[†]	S.E.
Constant	10.079***	0.047	10.007***	0.042
lnPseed	-0.067***	0.005	-0.069***	0.005
lnPfertilizer	-0.338***	0.009	-0.332***	0.007
lnPlabor	-0.209***	0.005	-0.180***	0.005

lnLand	1.046***	0.007	1.068***	0.006
lnCapital	-0.035***	0.006	-0.043***	0.006
Season 2	-0.268***	0.005	-0.261***	0.005
Season 3	-0.285***	0.005	-0.273***	0.005
Model properties				
Lambda (λ)	7.316***	0.004	11.906***	0.003
Sigma_u	0.097***	0.003	0.096***	0.003
Sigma_v	0.013***	0.002	0.008***	0.001
Log-likelihood	1,433.31		1,307.76	
Observations	957		841	

Note: ***, **, * represent significant levels at 1%, 5%, 10%, respectively.

Source: Author

In summary, Table 2.4 compares the profit efficiency between adopters and non-adopters estimated in all SF models. The result shows that HQRV adopters perform less profit-efficiently than non-adopters, and that profit efficiency gaps between the two groups are significantly underestimated if selection biases and technology gaps are not considered. Specifically, without controlling for any self-selection bias and technology gap (Model 1), the average profit efficiency scores for adopters and non-adopters are 0.67 and 0.70, respectively, with a profit efficiency gap of 4.6%. When selection bias from observable and unobservable factors was controlled (Model 4), the profit efficiency gap increased to around 9.5%, with mean profit efficiency scores of 0.68 for adopters and 0.75 for non-adopters. However, that direct comparison between the two groups is not accurate because it faces the problem of a technology gap. After correcting for the technology gap (MPE in Model 5), the mean profit efficiency for adopters and non-adopters are 0.61 and 0.72, with a profit efficiency gap of 15.4%.

Table 2.4 PE scores for adopters and non-adopters from SF models.

Model	Adopter		Non-adopter		Difference in mean	
	Mean	S.D.	Mean	S.D.	Mean (%)	*t*-statistic†
1. Full sample Pooled PE	0.67	0.21	0.70	0.15	-0.03 (-4.55%)	-2.76***
2. Matched sample Pooled PE	0.69	0.20	0.72	0.15	-0.03 (-4.06%)	-2.42**
3. Conventional PE	0.67	0.19	0.75	0.15	-0.08 (-10.64%)	-6.75***
4. Sample selection PE	0.68	0.19	0.75	0.15	-0.07 (-9.50%)	-6.12***
5. TGR	0.89	0.06	0.96	0.03	-0.07 (-6.87%)	-20.19***
MPE	0.61	0.17	0.72	0.14	-0.11 (-15.36%)	-9.90***
Observations	319		522			

Note: ***, **, * represent significant levels at 1%, 5%, 10%, respectively.

Source: Author

The difference in profit efficiency scores between the two groups is also shown in Figure 2.4, which presents the distribution of profit efficiency scores between HQRV adopters and non-adopters. The distribution for the adopter group is more dispersed to the lower value range, implying an overall lower profit efficiency performance than the non-adopter group. This suggests that there is statistical evidence supporting the negative impact of HQRVs on farmers' profit efficiencies.

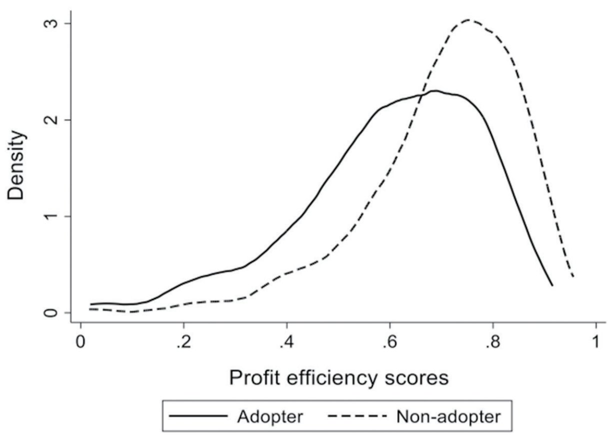

Figure 2.4 Distribution of profit efficiency scores for adopters and non-adopters.
Source: Author

The results from Table 2.5 show the effects of HQRV adoption on farmers' variable profit. The result shows that the difference in actual (observed) variable profit between adopters and non-adopters is around 10.5%. It is obvious that this profit gap is not as attractive as expected (around 30%). This can be a possible reason why the adoption rate of HQRV is not high. However, the underlying reason is that HQRV adopters perform less efficiently, which makes their profit efficiency lower than non-adopters. After correcting for self-selection biases arising from observed and unobserved heterogeneity and the technology gap, the profit gap increases to around 28%. Particularly, the maximum variable profit for adopters can be 1,741 USD/ha and higher by 28% compared to non-adopters (1,358 USD/ha). Currently, compared to the frontier, adopters can lose 655 USD/ha while non-adopters can lose 376 USD/ha.

Table 2.5 Effects of HQRV adoption on farmers' variable profit.

Variable	Adopter		Non-adopter		Difference	
	Mean	S.D.	Mean	S.D.	Mean	(%)†
Observed variable profit (USD/ha)	1,085	463	982	363	103	(10.49%)***
Frontier variable profit (USD/ha)	1,741	474	1,358	404	382	(28.12%)***
Variable profit loss (USD/ha)	655	272	376	192	279	(74.20%)***
Observations	319		522			

Note: ***, **, * represent significant levels at 1%, 5%, 10%, respectively.

Source: Author

6. Conclusion

This study analyzes the impacts of HQRVs on rice farmers' profit and profit efficiency performance and investigates the determinants of HQRV adoption decisions.

The results show that farm size, rice plots, contract farming, regions, and seasons significantly influence HQRV adoption decisions. The observed variable profit of HQRVs (per ha) is only 10.5% higher than that of conventional varieties, not as high as expected. This is explained by the fact that HQRV adopters perform 15.4% less efficiently (0.61) than non-adopters (0.72). If inefficiency were eliminated, HQRV adopters could achieve around 28% (382 USD/ha) higher variable profit than non-adopters.

The results suggest that to better exploit the potential of HQRVs, policies should be targeted to improve rice farmers' profit inefficiency and promote the adoption of HQRVs. The findings recommend that policies should consider increasing farm size and contract farming to promote the adoption of HQRVs. In addition, HQRVs should be developed to be better adapted to adverse production conditions.

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Chapter 2. Impact of High-Quality Rice Variety on Profit and Profit Efficiency: Evidence from Vietnam

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