Credit Accessibility, Risk Attitude, and Social Learning: Investment Decisions of Aquaculture in Rural Indonesia

Sachiko Miyata* and Yasuyuki Sawada**

* International Food Policy Research Institute, Markets, Trade, and Institutions Division
2033 K Street, N.W. Washington D.C. 20006 USA

** University of Tokyo, Faculty of Economics
7-3-1 Hongo Bunkyo-ku, Tokyo, 113-0033 Japan

Poster paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18, 2006

1. Introduction

This paper presents a theoretical and empirical investigation of the micro-structure of a technological adoption process by examining the actual decisions made by households in Indonesia. In terms of theory, there are three factors which may affect an individual's decision to adopt a technology. First, the experience of others may affect a person's technological adoption decision (Foster and Rosenzweig, 1995). Second, a new investment may be regarded as a high risk - high return activity, and the degree of individual risk aversion will affect the adoption decision. Existing studies using experiments (Binswanger, 1980), econometric analysis (Fafchamps and Pender, 1997), and area studies (Scott, 1976) have shown that farmers in developing countries are typically risk averse. When risk-averse households are unable to insure themselves against income shocks, they tend to shy away from risky activities. Finally, adopting new technology usually involves a large initial investment. The accessibility of credit markets acts as a decisive factor in financing the large fixed cost of a new investment.

This paper compares these different factors using empirical data with the aid of a consistent theoretical framework. To this aim, we employ household survey data from the floating net aquaculture (hereafter, FN) business that was introduced in villages surrounding a dam reservoir constructed in Saguling, Indonesia in 1985. We interviewed approximately 400 households in the villages and collect their retrospective information over a period of 16 years exclusively for this study. Also, following the approach of Binswanger (1980), we conducted investment experiments in order to quantify the degree of risk aversion by village members directly.

We believe this paper contributes to the existing literature as our analysis is the first to examine empirically these three different determinants of household investment behavior in an integrated dynamic framework in the context of a developing country. Our findings show that all three of the above hypotheses are verified in the empirical analysis. Moreover, using bivariate probit analysis is verified since the coefficient correlation of disturbances is significant. Our marginal effect analysis shows that credit constraint and risk attitude critically reduces the probability of adopting the new FN technology.

2. Village Background

For the empirical analysis in this paper, we conducted household surveys in the villages around Saguling Dam in county Bandung in Indonesia. Saguling dam is located between Jakarta and Bandung cities, approximately 30km from Bandung (Figure 1). This dam was constructed in 1985. For those who were relocated, one of the most important supplementary income sources was floating net aquaculture (FN). FN brought some economic benefits to the local people, but required financial and physical investments by households to implement it. This was the first large-scale implementation of the floating net cage technique in Indonesia, and very few people started FN in the beginning since the FN were totally new to the local people (Costa-Pierce and Soemarwoto ed., 1990). However, early pioneers attended the training sessions and started FN around 1986. Subsequently it diffused rapidly in Saguling, and by 1995 FN had expanded to 20 locations in Saguling. However, there is some controversy as to whether the project was beneficial overall to the resettled people or the poor, and many questions have been raised. Hence, it is important to carefully identify the factors that produced successful FN investments.

3. The Model Framework

We will employ a quantitative analysis of the structure of FN investments in order to make a formal assessment of relative importance of these different determinants. The first step is to construct an integrated theoretical model of FN investments. Then we will test statistically the restrictions derived from the theory.

When there are two investment opportunities, one with high risk and high return and the other with low risk and low return, a household's attitude toward risk matters. A risk-averse household will optimally decline a high-risk investment although it can generate a high return if the risks are understood and managed properly. On the other hand, less risk-averse households will undertake a profitable investment regardless of its riskiness.

Poor households usually have only a limited access to credit markets and are constrained from borrowing for a variety of reasons such as high information cost (Stiglitz and Weiss, 1981) or lack of assets for collateral (Carter, 1988). The existence of credit constraints has important negative impacts on FN investments by poor households, since credit-constrained households cannot afford the initial investment required to start up an FN business. The initial cost with minimum 1 unit is at least between 400,000 and 800,000 Rupiah (in late 1980's)[1], which is more than several months income in the area. Therefore, if there is no credit available, a household will choose not to invest in FN.

By extending the models developed by Eswaran and Kotwal (1989) and Morduch (1994), we construct a simple household model of FN investments which integrates the three determinants mentioned above, i.e., social learning, risk aversion, and credit accessibility. We implicitly derive the optimal solution to the household's investment problem of maximization problem of expected utility (Miyata and Sawada, 2002) as:

$$I^* = I[p(N), \gamma, B; R, S, e]. \tag{1}$$

This equation (1) indicates that the optimal FN investment I^* is a function of the probability of the high-return state $p(N)$, which depends on the number of successful investors in the network N, attitude toward risks γ and credit availability B as well as returns R and S from the investments. Note that the probability of the high-return state, $p(N)$, can be either a positive or negative function of the number of existing successful investors, N. If it is a positive function, it can be attributed to leaning effects from others, i.e., positive social learning. If saturation effects in FN investments are serious, the probability can be a negative function of N.

[1] In 1988, an initial investment of Rp 1 million (more or less US \$560; US \$1 = Rp 1,785, rate at the time of 1988) was

By differentiating the first-order condition for the household problem (Miyata and Sawada, 2002), we can show that

$$\frac{dI^*}{dN} \gtrless 0 \quad if \quad \frac{dp}{dN} \gtrless 0, \tag{2}$$

$$\frac{dI^*}{d\gamma} < 0, \tag{3}$$

$$\frac{dI^*}{dB} > 0. \tag{4}$$

Equation (2) indicates that if there is a positive social learning effect from a network, knowing previous successful investors will encourage investments in the new technology, and visa versa. Yet, as can be seen from equation (3), adoption of the new technology may depend on risk preferences. Equation (4) demonstrates that access to credit positively affects the extent to which risky technologies are adopted (first derived in Proposition 1 of Eswaran and Kotwal, 1989). Equation (2), (3), and (4) represent theoretical restrictions which can be examined empirically. It is also easily verified that the credit ceiling does not affect investment decisions when the credit constraint is not binding.

4. Empirical Framework

In order to set up an empirical model for FN investments, we linearize equation (1) to obtain:

$$I^* = \alpha_0 + \alpha_N N + \alpha_\gamma \gamma + \alpha_B B + X\beta + u \ , \tag{5}$$

where X is a matrix of household characteristics such as household head's age, household income and assets, which is included as a set of control variables. The last term in the right hand side, u, denotes a well-behaved error term. Since the resource allocation to FN investments, I*, is

---

needed to invest in aquaculture (Costa-Pierce and Soemarwoto, 1990).

unobservable latent variable, we employ a binary dependent variable model to estimate equation (5).

Investment with Endogenous Credit Constraints

Our econometric model is composed of two interrelated probit models—the first probit model for FN adoption composes of the binary response model of equations (5). The second probit equation is for credit constraint consists of equations (6), (7) and (8) (Jappelli, 1990). If we assume that ε and u follow standard bivariate normal distribution, then the model becomes a version of the bivariate probit model (Greene, 2000):

$$I^* = \alpha_0 + \alpha_N N + \alpha_{\gamma}\square + \alpha_{cc} cc + X\beta + u \ ,$$

$$v = 1 \quad if \quad I^* > 0, \tag{5'}$$

$$v = 0 \quad otherwise.$$

$$H^* = Z\pi + \varepsilon \ , \tag{6}$$

$$cc = 1 \quad if \quad H^* < 0, \tag{7}$$

$$cc = 0 \quad otherwise. \tag{8}$$

where $E(u) = 0$ and $E(\varepsilon) = 0$.

If an unobserved component of the credit constrained variable, ε, is systematically correlated with unobserved characteristics, u, which influence FN adoption, there will be an endogeneity problem. Hence, to estimate parameters of this model where cov(ε, u) ≠ 0, we employ the full information maximum likelihood (FIML) method. (For the details, see Miyata and Sawada, 2002)

In equations (5'), (6), (7) and (8), we need to impose the conditions var(ε) = 1 and var(u) = 1 for identification. With the econometric model above, we cope with the endogeneity problem of credit constraints explicitly. Since the estimated coefficients of the results do not reflect the magnitude of each variable, we estimate marginal effects to examine the degree of the independent variables' influences on the likelihood of FN adoption (Greene, 2002).

5. Data

From previous household-level surveys, the average income of households in these villages was determined to be 300,000 to 400,000 Rupiah (Rp) (approximately US23.5 to 51 dollars) per month, although many were well below this range (Miyata, 2003). This income level is around the poverty line and it is considered poor by international standards[2]. The first village (Village A) was chosen because an individual pioneer had implemented FN early and village A had become one of the most active FN villages. Village B was much less active and was chosen for comparison purposes. 400 households were selected by random sample within three different wealth strata[3]. The village head and local government officers in each village categorized all households into three groups; rich, middle, and poor, based on their subjective assessments of each household's asset ownership, income, and occupation. These households were interviewed individually so that we could collect their FN investment behavior and socio-economic information between 1985 and 2000. In order to gather direct information about a given household's risk attitudes, we used a refined version of a stochastic investment game. Detailed procedures of our experiments, econometric specifications and our estimation results of risk aversion functions are summarized in Miyata (2003).

Variables

As control variables to estimate our investment equation, i.e., a set of variables, $\underline{X}$, in equation (5'), we include various household physical and human asset variables. Specifically, these independent variables are the number of members of the household (*Num_hh*), the age of the respondent (*Age*), the years of schooling for the most educated member of the household

---

[2] Poverty line in rural Indonesia estimated roughly between 74000 Rp and 81200Rp per person.

[3] The village head and local government officers in each village categorized all households into three groups; rich, middle, and poor, based on their subjective assessments of each household's asset ownership, income, and occupation.

(*High_edu*), the footprint of the house in 100 square meters (*Hslnd100*), farm land in 100 square meters (*Farm100*), and the monthly income (in million Rp) (*Income*).

The dummy variable *FN* takes 1 if the respondent is engaging in FN aquaculture and 0 if not. *Village* is 1 for households from village A and 0 for village B. *Resettle* is 1 if the household was resettled due to the construction of the Saguling Dam. *Risk* is the risk aversion coefficient obtained from the experimental results in 2000. *CC* dummy takes 1 if the household is credit constrained, and 0 otherwise. *FN training* dummy takes 1 if the household has ever received aquaculture training in the past, and 0 if not. *Success* is the number of successful FN owners the household knew when it adopted FN.

Table 1 shows the descriptive statistics of these dependent and independent variables used in our estimation. Note that Table 1 shows the summary statistics of the pooled data from 1985 to 2000. The respondents have an average of 6 years of schooling. The mean of 'highest years of education' is higher than the average respondent's education, implying that their children may have a higher level of education than the respondent. The other personal characteristics such as age, occupation, etc. vary widely across the sample.

6. Estimation Results

The bivariate probit estimation results are presented in Table 2. We show three estimation results based on different specifications in order to check the robustness of the results. The signs of most coefficients are consistent across different specifications, including the variables for three main hypotheses of FN adoption factors, i.e., risk aversion, credit constraint, and learning effect. The robustness of our model is verified based on the consistency of the estimation results.

Our discussion is based on the result of the specification (3) in Table 3, in which we employed income and asset variables as identifying instrumental variables for the credit constraint equation of a household. The coefficient correlation of disturbances, , for this specification (3) is

-0.831 with standard of error of 0.085. The Wald test of null hypothesis, = 0, is rejected at the 1% significant level. This supports the validity of employing the bivariate probit model for estimation. The negative sign of the coefficient indicates that an unobservable factor that shifts a household toward credit constraints and an unobservable factor that promotes FN adoption are inversely correlated.

According to the FN investment model results of the specification (3) in Table 2, all of the three hypotheses are supported statistically. First, the coefficient of the risk aversion variable is significantly negative at the 1% level, implying that when households become more risk averse, they are less likely to adopt FN. Second, the credit accessibility variable has a negative and statistically significant coefficient. This result indicates that when a household loses credit accessibility, it decreases the probability of adopting FN significantly.

Finally, with respect to the learning effects, several findings emerged from the estimations. First, the estimated coefficient of the number of successful FN owners known by the household has a positive and statistically significant coefficient. This result strongly supports the social learning hypothesis, i.e. when household knows more people who are successful in the FN business, it raises the probability of their adopting FN. Second, the coefficient of the year dummy becomes gradually larger in the later years, especially in 1999 and 2000, implying that the accumulated experiences in the whole area had positive effects on individual-level FN adoptions. Across the whole Saguling reservoir area, villages have accumulated expertise in the FN business. As we have seen in the model framework of equation (2), if learning has positive effect, then later years would raise the probability of adopting FN. Attending FN trainings also raises the probability of adopting FN significantly. Other variables such as household education level also raise the likelihood of FN adoption.

In Table 2, the results of the credit constraint equations are also consistent with theoretical predictions. Higher education, larger income and greater land assets decrease the likelihood of household being credit constrained. Households in village A are less likely to be credit constrained, and this fact may explain the reasons why people in village A became more active in FN than those in village B.

Table 3 shows the marginal effects of the marginal probability of credit constraints and FN adoption when the independent variables are at their means. The strongest marginal effect for adopting FN appears to be generated by credit constrained dummy. The credit accessibility enhances the probably of adopting FN by 3.91%, whose coefficient is the largest coefficient among all the variables. Similarly, a household with one unit lower risk aversion has a 2.96% higher probability of FN adoption, and one which attended a training session has a 1.24% higher probability.

However, the learning effect from others' success seems to have a very small marginal effect. Even knowing 100 successful FN people only raises the likelihood of FN adoption by 2%. The learning effect from others is smaller than the credit constraint or risk attitude. The variable resettled only raises the probability of adopting FN by 0.03 %. Although the FN aquaculture was aimed at resettled people, they did not really benefit from it. Among the marginal probabilities for credit constraint of a household, it appears that the most important variable is risk attitude.

7. Conclusion

Our bivariate probit results suggest that credit constraint, risk attitudes, and social learning all affect the Indonesian household's decision to adopt the new FN technology and the results are highly robust. Among other things, our statistical tests showed that credit constraints act as a serious constraint for households to adopt FN. This is fully consistent with the anecdotal evidence from the field, i.e., without capital, there is no way to implement FN. Our results are also in accordance with the findings of the previous Saguling studies that the poor could not have benefited due to a lack of access to capital (Manatunge et al, 1999).

Our findings provide important policy implications not only for rural Indonesia but also for other areas in similar situations. First, when introducing and promoting a new technology such as aquaculture, which requires a high initial fixed investment cost, supplementary programs that ease credit constraints are important to the successful adoption of the new technology. Reducing the burden of obtaining credit is indispensable especially if the program is targeted to the poor since our results showed that credit constrained households typically own less land assets and have lower income. Some studies suggest that the poorest may not have benefited from FN due to their inability to secure ownership of the FN cages (Manatunge et al, 1999). The poor's credit accessibility seems to be the key to improving their current situation.

The recent trend to focus on micro credit schemes in developing countries is in accord with this finding. Although Indonesia has a long history of micro-finance and various micro credit schemes (Robinson, 2002), the surveyed villages did not seem to benefit fully from these programs. There were hardly any organizations involved in these villages for providing micro credit. In Indonesia, improvements in credit accessibility has been recognized as one of the most critical issues in development projects as evidenced by the Indonesian government launching micro credit programs in late 1990's in cooperation with the World Bank[4]. While our results strongly support this policy direction, formal recognition of credit limitations as a primary issue is only beginning to emerge at the national level. Second, providing opportunities for local people to attend various training programs, obtain technical assistance, or consult with experienced participants would help to reduce the unnecessary caution against trying a profitable new technology.

[4] For example, there has been a nationwide project called 'Kecamatan Development Project' in Indonesia supported by IBRD and IDA. The project includes micro credit lent to village group members for working capital.

References

Binswanger, H., "Attitudes towards Risk: Experimental Measurement in Rural India," *American Journal of Agricultural Economics* 62(3), (1980), 395-407.

Carter, M., "Equilibrium Credit Rationing of Small Farm Agriculture," *Journal of Development Economics* 23, (1988), 83-103.

Costa-Pierce B. A. and O. Soemarwoto ed., *Reservoir Fisheries and Aquaculture Development for Resettlement in Indonesia,* (International Center for Living Aquatic Resources Management, Manila, 1990).

Eswaran, M. and A. Kotwal, "Credit as Insurance in Agrarian Economies," *Journal of Development Economics* 31, (1989), 37-53.

Fafchamps, M., and J. Pender, "Precautionary Saving, Credit Constraints, and Irreversible Investment: Theory and Evidence From Semiarid India," *Journal of Business and Economic Statistics* 15 (2), (1997), 180-194.

Foster, A. D., and M. R. Rosenzweig, "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *Journal of Political Economy* 103, no.6, (1995), 1176-1209.

Greene, W. H., *Econometric Analysis*, 4th ed., (Prentice Hall, 2000).

Jappelli, T., "Who is Credit Constrained in the U. S. Economy?, " *Quarterly Journal of Economics*, 105, no. 1 (1990), 219-234.

Manatunge, J. et al., "Securing Ownership in Aquaculture Development by Alternative Technology: A Case Study of the Saguling Reservoir, West Java," *International Journal of Water Resources Development Journal* 17, no. 4, (1999), 611-631.

Miyata, S., "Household's Risk Attitudes in Indonesian Villages," *Applied Economics,* 35, (2003), 573-584.

Miyata, S., and Y. Sawada, "Investment under Uncertainty: Lessons from Aquaculture in Indonesia," *8th Convention of East Asian Economic Association*, Kuala Lumpur, 4-5 November (2002).

Morduch, J., "Poverty and Vulnerability," *AEA Paper and Proceedings*, 84, no. 2, (1994), 221-225.

Robinson, M. S. *The Microfinance Revolution vol.2: Lessons from Indonesia*, May, (World Bank, Washington D.C., 2002)

Scott J. *The Moral Economy of the Peasant: Rebellion and Subsistence in Southeast Asia*, (Yale University Press, 1976)

Stiglitz, J. E. and A. Weiss, "Credit Rationing in Markets with Imperfect Information," *American Economic Review* 71, (1981), 393-419.

Table 1
Summary Statistics

Variable name	Mean	Standard. Deviation
Dependent variable		
FN adoption dummy (adopted=1)	0.12	0.33
Independent variables		
Number of members in a Household	3.96	1.76
Age of respondent	41.23	13.55
Village dummy (Village A=1, B=0)	0.69	0.46
Resettled dummy (resettled=1)	0.30	0.46
Respondent's years of schooling	5.82	2.95
Highest years of schooling in Household	7.02	2.93
Monthly income (Rupiah)	89397.98	327048.40
House land (m^2)	165.95	231.61
Farm land (m^2)	242.61	1219.89
Estimated degree of risk aversion	-1.02	0.35
Credit Constrained dummy (yes=1)	0.85	0.36
Number of Successful FN ownerFN training dummy (attended=1)	1.350.62	5.170.24
Number of Successful FN owner	1.35	5.17
Number of valid observations	5254	

Table 2
Bivariate Probit Model Estimation of Household Credit Constraint and FN Adoption

		Specification (1)				Specification (2)			
		Credit constraint equation		FN investment equation		Credit constraint equation		FN investment equation	
Variable Definition	Name	*cc*	Std. error	*v*	Std. error	*cc*	Std. error	*v*	Std. error
Number of household member	Numhh	0.167	(0.02)***	-0.385	(0.05)***	0.167	(0.19)***	-0.395	(0.05)***
Age of respondent	Age	0.085	(0.01)***	-0.030	(0.005)***	0.079	(0.01)***	0.023	(0.03)
Age squared divided by 100	Age2_100	-0.075	(0.01)***			-0.069	(0.01)***	-0.063	(0.04)
Village (A=1, B=0)	Village	-0.247	(0.06)***	0.426	(0.13)***	-0.252	(0.06)***	0.481	(0.13)***
Resettled dummy	Resettle	-0.464	(0.06)***	0.069	(0.17)	-0.466	(0.06)***	0.046	(0.15)
Highest years of schooling	high_edu	-0.139	(0.05)***	0.195	(0.09)**	-0.144	(0.05)***	0.236	(0.10)**
Highest years of schooling squared	highedu2	0.017	(0.003)***	-0.028	(0.005)***	0.017	(0.003)***	-0.030	(0.01)***
Income (in 1,000,000 Rupiah)	Income	-0.414	(0.08)***	-0.149	(0.17)	-0.438	(0.08)***	-	
House land divided by 100	Hslnd100	-0.103	(0.01)***	0.008	(0.03)	-0.101	(0.01)***	-	
Farm land divided by 100	Farm100	0.003	(0.003)	0.014	(0.005)***	0.005	(0.003)	-	
Respondent's risk aversion	Risk	2.515	(0.13)***	-4.812	(0.45)***	2.502	(0.13)***	-4.807	(0.34)***
Credit constrained (yes=1)	Cc			-1.097	(0.58)*			-1.301	(0.45)***
FN training dummy, (attended =1)	Fn_train			0.648	(0.21)***			0.742	(0.19)***
Number of successful FN owner	Success			0.033	(0.01)***			0.036	(0.01)***
year 1986	Yr2	0.216	(0.18)	-0.018	(0.36)	0.218	(0.18)	-0.002	(0.37)
year 1987	Yr3	0.096	(0.17)	0.046	(0.33)	0.097	(0.17)	0.052	(0.35)
year 1988	Yr4	0.185	(0.17)	0.070	(0.34)	0.186	(0.17)	0.062	(0.35)
year 1989	Yr5	0.202	(0.17)	0.037	(0.34)	0.201	(0.17)	0.039	(0.36)
year 1990	Yr6	0.066	(0.16)	0.455	(0.32)	0.066	(0.16)	0.464	(0.33)
year 1991	Yr7	0.079	(0.16)	0.528	(0.32)	0.079	(0.16)	0.542	(0.33)
year 1992	Yr8	0.014	(0.16)	0.587	(0.31)*	0.016	(0.16)	0.615	(0.32)*
year 1993	Yr9	-0.007	(0.16)	0.582	(0.32)*	-0.003	(0.16)	0.625	(0.33)*
year 1994	Yr10	0.013	(0.16)	0.721	(0.33)**	0.017	(0.16)	0.757	(0.33)**
year 1995	Yr11	-0.092	(0.15)	0.607	(0.30)**	-0.089	(0.15)	0.609	(0.31)*
year 1996	Yr12	-0.086	(0.15)	0.510	(0.30)*	-0.084	(0.15)	0.523	(0.31)*
year 1997	Yr13	-0.067	(0.15)	0.349	(0.30)	-0.063	(0.15)	0.336	(0.31)
year 1998	Yr14	0.038	(0.16)	0.575	(0.32)*	0.043	(0.16)	0.597	(0.32)*
year 1999	Yr15	0.042	(0.16)	0.918	(0.34)***	0.047	(0.16)	0.961	(0.33)***
year 2000	Yr16	-0.073	(0.16)	0.837	(0.33)**	-0.072	(0.16)	0.915	(0.33)***
Constant	Constant	1.705	(0.33)***	-4.505	(0.51)***	1.842	(0.33)***	-5.620	(0.87)***
r				-0.867	(0.10) **			-0.831	(0.09)***

Note: Result is based on 4946 Observations (Standard error in Parentheses).
*, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 3

Marginal Effects on the Marginal and Joint Probability of Household Credit Constraint and FN Adoption Model

Name	Pr[cc =1]	Pr[v =1]
Reference probability	0.9237	0.0019
Numhh	0.0240	-0.0024
Age	0.0113	0.0001
Age2_100	-0.0098	-0.0004
Village	-0.0336	0.0024
Resettle	0.0770	0.0003
High_edu	-0.0206	0.0015
Highedu2	0.0024	-0.0002
Income	-0.0628	
Hslnd100	-0.0145	
Farm100	0.0007	
Risk	0.3589	-0.0296
Cc		-0.0391
Fn_train		0.0124
Success		0.0002
Yr2	0.0272	0.0000
Yr3	0.0131	0.0003
Yr4	0.0236	0.0004
Yr5	0.0254	0.0003
Yr6	0.0091	0.0053
Yr7	0.0108	0.0069
Yr8	0.0022	0.0087
Yr9	-0.0004	0.0089
Yr10	0.0024	0.0130
Yr11	-0.0135	0.0085
Yr12	-0.0127	0.0065
Yr13	-0.0094	0.0032
Yr14	0.0060	0.0082
Yr15	0.0066	0.0216
Yr16	-0.0108	0.0195
Yr16	-0.0108	0.0195

Note : Marginal effects based on equation (2) in Table 2

Figure 1

Map of Survey Site