Rise and Fall of New Technology: Quasi-experimental Evidence from a Developing Country

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Abstract

This paper investigates a new technology's long-term processes of adoption, standardization, and decline. Specifically, we examine the decision to invest in floating net aquaculture, introduced as a social safeguard program for poor Indonesian households that were involuntarily resettled because of a dam/reservoir construction project. We find the program helped transform and sustain the livelihood of resettlers by facilitating the adoption of this new technology. We also find behavioral irreversibility in technology adoption, resulting in overfishing in the reservoir. Considering the increasing importance of hydropower and renewable energy sources, this innovative resettlement program provides critical policy insights.

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Technology adoption plays a fundamental role in economic development (Aghion and Howitt, 2009; Comin and Hobijn, 2010) and has a number of important determinants, depending on the context and point in time (Foster and Rosenzweig, 2010; Mobarak and Saldanha, 2022). Such determinants include the profitability of the technology (Suri, 2011), skills and human capital (Schultz, 1975; Foster and Rosenzweig, 1995), social learning (Banerjee, 1992; Conley and Udry, 2010; BenYishay and Mobarak, 2018; Beaman et al., 2021), ownership of collateralizable assets (e.g., land, access to credit, and insurance) (Miyata and Sawada, 2006; Gine and Klonner, 2008; Giné and Yang, 2009; Farrin and Miranda, 2015), and risk and time preferences (Liu, 2013; De Groote and Verboven, 2019). Recent studies have revealed that the adoption of potentially beneficial technologies has been impeded by a variety of behavioral biases (Kremer, Rao and Schilbach, 2019) such as hyperbolic discounting (Duflo, Kremer and Robinson, 2011), loss aversion and probability weighting (Tanaka, Camerer and Nguyen, 2010; Liu, 2013), and limited attention (Hanna, Mullainathan and Schwartzstein, 2014).

Despite their important contributions, existing studies have basically examined the temporal nature of technology adoption, leaving its long-term dynamic process largely underinvestigated. To bridge this important gap in the literature, this study examines the long-term dynamics of technology adoption over 25 years in a natural experimental setting caused by the construction of a dam in Indonesia. By doing so, we make an important contribution because understanding technology adoption in the context of a country's long-term sustainable economic growth requires acknowledging the dynamics of the technology adoption process in the long run. The seminal work of Griliches (1957) was the first to show that adopting a new technology generally follows an S-shaped curve in the long run, where the major period of rapid adoption occurs only after an initially slow take-up (Geroski, 2000; Wejnert, 2002). While there exists rich academic literature on the S-shaped curve in disciplines outside economics, to the best of our knowledge, rigorous empirical microeconomic studies are scarce, especially in the context of a developing country.

Against this background, this study empirically examines the long-term adoption of freshwater aquaculture technology in Indonesian villages. Farmers in these villages have lost their homes and farmlands owing to the construction of a dam and subsequent land submergence. They have been involuntarily resettled and have unexpectedly changed their occupations from agriculture. To help such farmers, floating net aquaculture (FNA) has been introduced by local universities, research centers, governments, and international organizations as an innovative social safeguard program to help farmers rebuild their livelihoods (Sunardi et al., 2013). This setting provides us with a clean, natural experiment in which we can exploit exogenous variations in asset loss to identify the causal relationship between the loss of productive assets and the adoption of the new technology.

Our findings support the role of this social safeguard program in partially transforming and sustaining resettler livelihoods, thereby mitigating the potential negative consequences of the resettlement program. In fact, whether the project has benefitted resettled people, especially the poor, has been controversial (Nakayama et al., 2000; Sunardi et al., 2013). Hence, the findings of our study provide concrete evidence of the project's benefits and bottlenecks in facilitating FNA investment. This implication allows policymakers to redefine the objectives of the resettlement project.

Three other key findings are noteworthy. First, social learning, a low subjective discount rate, and human capital play key roles in technology adoption in the initial stage. Second, 15 years after the new technology was introduced, it became standardized, meaning that specific skills or resources were no longer needed to adopt it. Simultaneously, real profits from using the technology have declined continuously, which can partly be attributed to the deterioration in water quality due to excessive fish farming during the early stage. This implies the occurrence of "the tragedy of the commons" in the reservoir area. Third, while initial adopters exited continuously during the later stage, those who have broad social networks and a high risk tolerance, remained users of the technology in the long run. We also find that initial adopters with hyperbolic preferences were less likely to withdraw from the technology. This finding suggests that behavioral irreversibility in technology adoption and the resulting overfishing in the reservoir may drive the tragedy of the commons.

Our study thus makes a novel contribution to the literature by showing the long-term changes in the nature of a new technology in the field. Considering the increasing importance of hydropower in the transition to renewable energy sources, this innovative resettlement program following a dam construction project will provide critical policy insights in making such projects sustainable.

1 Background and Research Strategy

We design and conduct household panel surveys in Indonesia, focusing on households' long-term adoption of FNA after their unexpected relocation because of a dam/reservoir construction project.

1.1 Study Background

Our study site is the area around the Saguling Dam in Bandung county (Kabupaten) of Cililin district (Kecamatan) in Indonesia. The dam is located between the capital city Jakarta and Bandung city, approximately 30 km from Bandung (online Appendix Figure B.1). The dam construction began in 1983 and the reservoir was filled in 1985. Although the dam was constructed mainly to provide hydroelectric power, it is also used for water supply and aquaculture. The construction of the dam displaced nearly 14,000 people across more than 3,000 households (Costa-Pierce and Soemarwoto, 1990).

As a social safeguard program for those relocated, FNA was introduced by the local provincial government in partnership with two local university institutes, namely, the Institute of Ecology at the Padjadjaran University and the International Center for Living Aquatic Resources Management (ICLARM).[1]. With the support from these institutions as well as the government and World Bank, FNA was prioritized as one of the most important and innovative supplementary income sources for involuntary resettlers in the villages surrounding the newly constructed dam and reservoir. Indeed, this

[1]The ICLARM is now called the World Fish Center.

social safeguard program was the first to demonstrate the potential of a planned, integrated ecosystem approach to resettlement (Costa-Pierce, 1997). However, while the World Bank concluded that the dam project successfully relocated the affected population (Costa-Pierce, 1997, 1998), others criticized that the compensatory social safeguard program did not necessarily benefit involuntary resettlers sufficiently (Nakayama, 1998). This highlights the importance of rigorously evaluating the effectiveness of aquaculture programs.

In our study, we conducted two decennial household panel surveys in two villages located around the Saguling reservoir. The first household survey was conducted in these villages between February and April 2000. The second follow-up survey was conducted in February 2010 to track the same respondents from 2000 survey. We choose neighboring villages that have similar accessibility to road infrastructure and water quality, but different FNA investment levels. This information was provided by the local fishery offices, village offices, experts, and researchers from the Padjadjaran University. The first village is among the most seriously affected in terms of the number of relocated families (Suwartapradja et al., 1985). In this village, a pioneer adopted FNA at a very early stage, making it one of the most active FNA villages. The second village is much less active in FNA investment and is chosen for comparison purposes.

To select respondents, we employ a stratified random sampling scheme based on a list of all households in the two villages. First, we asked the village heads and local government officers in each village to categorize households into three groups based on a subjective assessment of their asset ownership, income, and occupation: rich, middle, and poor households. A total of 399 representative households were selected from each of these three categories. From February to April 2000, these households were interviewed individually to collect information on their FNA adoption behavior and socioeconomic characteristics from 1985 to 2000. [2] According to the data, average monthly income per capita in these villages in the year 2000 is 65,217–86,957 Rupiah (Miyata, 2003). Using the PPP from the World Bank's PovcalNet (3892.22 Rupiah per USD), monthly per

[2] In addition to contemporaneous data collected from the surveys, we use retrospective information on FNA adoption and variables used for the baseline balancing tests.

capita income ranges from USD 16.8 to 22.3 in the year 2000. In the surveyed villages, these values are well below the international poverty line, set at USD 1.9 per day or USD 57 per month. The second wave of the panel survey was conducted in February 2010, collecting information on households' FNA adoption behavior and socioeconomic characteristics from 2000 to 2010.

1.2 Empirical Framework

To investigate the determinants of long-term FNA adoption, we follow Maddala (1986) and Sawada and Lokshin (2009) to build a 25-year two-stage investment decision model in which the first stage runs from 1985 to 2000 and the second stage from 2000 to 2010. Figure 1 shows the sequential decision tree of individual i, where $D_{i,t}$ is a binary variable of the FNA adoption decision in stage t: $D_{i,t}$=1 if adopted at least once during stage t and 0 otherwise. Of the original 399 respondents, 254 households adopt FNA between 1985 and 2000, of which 127 continue to use it in the second stage, while 127 stop investing in FNA. Of the initial 145 non-adopters, the majority (131 households) remain non-adopters. Only 14 respondents start FNA for the first time in the second stage (Figure 1).

Formally, the first-stage decision is represented by the following simple binary dependent variable model:

$$D_{i,1} = 1[X_{i,1}\gamma > u_i], \tag{1}$$

where 1[.] is an indicator function that takes the value of one if the argument is true. $X_{i,1}$ is a set of independent variables that determine the FNA investment decision in the first stage. Following Angrist and Pischke (2008), we estimate this as a linear probability model by assuming that u_i follows a uniform distribution.

The second-stage FNA decision, covering 2000 to 2010, is also modeled as a binary investment decision conditional on the first-stage decision. Assuming two sequential linear probability models, we can apply the linear probability selection framework of

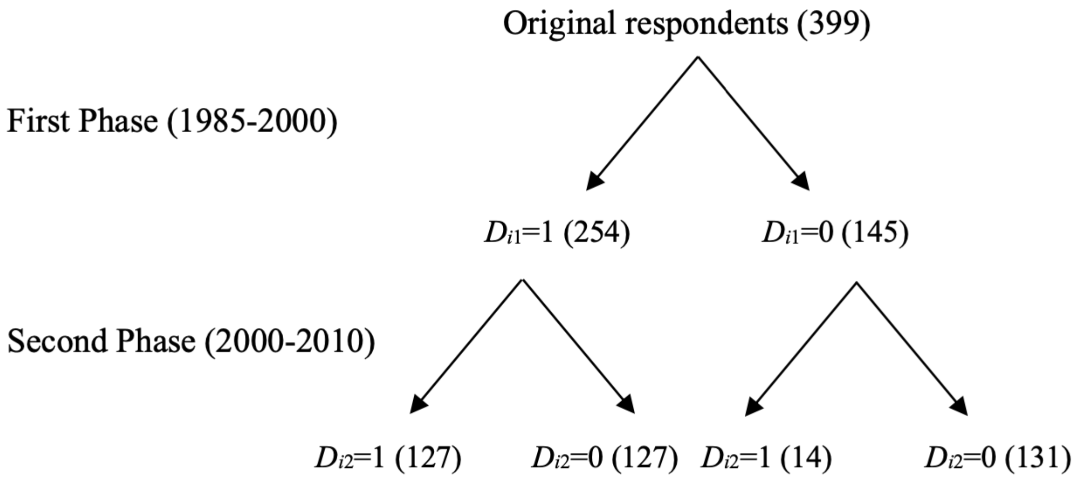

Figure 1. SEQUENTIAL DECISION TREE
The numbers in parentheses indicate the number of households that made the respective decisions.

Olsen (1980) as follows:

$$D_{i,2} = X_{i,2}\beta_y + \delta_y(X_{i,1}\gamma - 1) + \nu_{yi} \quad if \quad D_{i,1} = 1, \tag{2}$$

where the second term on the right-hand side shows the selection correction terms for those who adopted FNA in the first stage, that is, $D_{i,1} = 1$. Note that $E(D_{i2}|u_i < X_{i,1}\gamma) = X_{i,2}\beta_y + Cov(D_{i2}, u_i)\sqrt{3}(X_{i,1}\gamma - 1)$, where $Var(u_i)$ is normalized to one. For non-adopters in the first stage (i.e., $D_{i,1} = 0$), we build the following second-stage decision model:

$$D_{i,2} = X_{i,2}\beta_n + \delta_n(-X_{i,1}\gamma) + \nu_{ni} \quad if \quad D_{i,1} = 0, \tag{3}$$

where the correction term is the second term on the right-hand side based on the following formula: $E(D_{i2}|u_i > X_{i,1}\gamma) = X_{i,2}\beta_n + Cov(D_{i2}, u_i)\sqrt{3}(-X_{i,1}\gamma)$. Our empirical strategy is to primarily estimate the first-stage decision of equation (1) using the linear probability model and then stack the sequential decision models of equations (2) and (3) to estimate them together. The consolidated second-stage FNA decision model thus becomes

$$\begin{aligned} D_{i,2} =& D_{i,1}X_{i,2}\beta_y + (1 - D_{i,1})X_{i,2}\beta_n \\ &+ \delta_y D_{i,1}(X_{i,1}\gamma - 1) + \delta_n(1 - D_{i,1})(-X_{i,1}\gamma) + \nu_i. \end{aligned} \tag{4}$$

This model is estimated using the standard two-step procedure for a linear regression model after estimating equation (1) as the linear probability model. Because standard errors must be corrected, we estimate the entire procedure using the bootstrapping method.

As the determinants in this sequential decision model in the first and second stages, that is, $X_{i,1}$ and $X_{i,2}$, respectively, we first include indicator variables of exogenous home and farmland loss. To identify one of the critical determinants of technology adoption, we exploit the natural experimental setting in which the adoption of a new technology is encouraged for an exogenously selected subset of the population due to the dam construction. This is an unexpected situation, as local residents did not anticipate such a large dam to be constructed. Since these villagers were relocated from their original homes and farmland involuntarily, they had to switch from agriculture to other occupations, including FNA, which was an unknown, new technology back then (Nakayama, 1998).[3] This natural experimental setting can reveal the critical long-term process of real-world technology adoption.

Following existing studies, we also incorporate four other main factors of technology adoption: social learning (Banerjee, 1992; Conley and Udry, 2010; BenYishay and Mobarak, 2018; Beaman et al., 2021), risk attitude (Liu, 2013), exponential and hyperbolic discounts (Duflo, Kremer and Robinson, 2011; De Groote and Verboven, 2019; Kremer, Rao and Schilbach, 2019), and human capital (Schultz, 1975; Foster and Rosenzweig, 1995).

First, social learning is measured by the number of successful FNA owners each household is directly acquainted with. To understand the degree of acquaintance between the households and FNA owners, we asked questions about their relationship with these

[3]This FNA project was the first large-scale implementation of FNA in Indonesia. Almost no one adopted FNA at the beginning because it was a relatively new technology in 1985 (Costa-Pierce and Soemarwoto, 1990).

owners (family, relative, neighbor, colleague, or other).

Second, household risk attitudes are elicited by conducting lab-in-the-field experiments with the household heads.[4] To measure households' risk attitudes, we use a refined version of a hypothetical investment game without monetary incentives based on Binswanger (1980) in both 2000 and 2010. This allowed us to compute the risk aversion coefficients assuming a constant relative risk aversion utility function. The elicited coefficients are standardized across the 2000 and 2010 surveys to be comparable.[5]

Third, we measure exponential and hyperbolic discounting using multiple price list experiments. Specifically, we follow Pender (1996) for the 2000 survey and Ashraf, Karlan and Yin (2006) for the 2010 survey to construct separate binary variables of high exponential and hyperbolic discounters. The detailed payoff choices are summarized in Appendix A.

Finally, the human capital level, a critical determinant of the adoption of a new technology, is simply captured by collecting information regarding years of schooling in the surveys. As Foster and Rosenzweig (2010) discuss, education allows individuals to learn and decode new information accurately and efficiently, making them more likely to adopt a new technology.[6]

1.3 Descriptive Statistics and Baseline Balance

Online Appendix Table B.1 shows the descriptive statistics of the pooled data from the 2000 and 2010 surveys for the variables used in our estimation. The FNA adoption rate

[4]For earlier studies of risk experiments in developing countries, see Binswanger (1980).

[5]See Miyata (2003) for details on the risk experiment. Our experiments have slightly different stake sizes from those of Miyata (2003). For example, the lowest payoff in the 2000 (2010) game is 5000 (10,000) Rupiah.

[6]We also create a credit-constrained dummy from our data. Since more than 90% of respondents have credit constraints and there is no meaningful variation in this variable, we omit it from our empirical analysis. The details of this variable are as follows. To identify households facing credit constraints, we follow Scott (2000) and design the questionnaire carefully. Specifically, we ask two questions. First, for each year, we ask about the amount of credit a household obtains. For those who borrow money, we ask whether a household borrows as much as needed. If the answer is yes, we identify the household as unconstrained and credit-constrained otherwise. Second, we ask about the reasons for not obtaining credit among those who do not obtain credit. If a household does not need to borrow money, we classify it as non-credit-constrained, whereas if the household lists reasons such as fear of default or (expected) rejection, we classify it as a "discouraged borrower" that is credit constrained. According to our data, more than 90% of respondents are constrained in both the 2000 and the 2010 surveys. This indicates that most households lack collateral assets and thus are excluded from accessing credit.

(at least once) between 1985 and 2000, captured by the number of FNA adopters in these 15 years, reaches more than 60%, although this falls to 35% between 2000 and 2010. As Figure 2 shows, the initial surge in FNA investment decays over time, especially after 2000.

As noted earlier, we exploit exogenous variations created by involuntary resettlement due to the dam's construction. Specifically, we construct an indicator variable for displacement due to the dam's construction that takes the value 1 if a household lost all its landholdings and/or its home, and 0 otherwise. Of the 399 households, 51 fall into the former category. We also construct an indicator variable for inherited land ownership unaffected by the dam construction, with 57.1% of respondents inheriting land.

Regarding the potential social learning of FNA investment, the average number of known successful FNA owners is 3.7 in 1985, when FNA is first introduced, compared with 5.7 by 2000. The majority of respondents state that the number is less than 10.[7]

The mean proportion of hyperbolic discounters in the 2010 survey is higher than that in the 2000 survey (15.8% vs. 9.8%). The elicited exponential discounting shows a similar pattern: 45.9% of respondents in 2000 and 62.9% in 2010 are identified as impatient based on their preference for today's payoff over tomorrow's payoff.

As for the human capital variable, respondents have an average of 7.8 years of schooling, which corresponds to lower middle school education. However, the variation is also large, ranging from zero to a collegiate education. We further include three physical and human asset variables as control variables: household size (mean 4.6), the age of household heads (mean 56.7), and the size of the owned farmland (mean 0.28 ha).

Considering that household heads' years of schooling are unlikely to change, we use information from the first-stage survey conducted in 2000, which shows that no household heads were studying in that year. For the age variable, we use data from 2000 for the same reason. However, as the household head's age changes, there could arise shifts in generations, therefore we estimate an additional model based on a smaller cohort of

[7] Although the maximum number of successful FNA owners in 1985 is larger, its standard deviation in 2000 reduces to seven, suggesting that respondents from the 2010 survey earned significant income after many years of aquaculture experience. By contrast, some respondents to the 1985 survey may have counted all known FNA adopters as successful ones.

40–70-year-olds in 2000. If there is no generational shift, such cohorts would be aged 25–55 years in 1985 (i.e., the working age population). In our estimation, one of the key variables in online Appendix Table B.1, the risk aversion coefficient, is standardized with a mean of zero and a standard deviation of one.

Taking into account that the loss of a home due to involuntary resettlement serves as the source of the natural experiment, we perform baseline balancing tests to identify any causal relationships. Table 1 shows the descriptive statistics of the pre-resettlement variables classified by displacement status. The treatment group comprises those displaced and the control group comprises those whose land and home ownership is unaffected by the dam construction. All the standard deviations are clustered at the village level.[8] We compare the variables for those who had homes that were affected by the dam construction with the variables for those unaffected. The results show no difference in the mean values for all the variables except age. Since land submergence due to the dam construction occurs at the lowest altitude, it is natural that older people, who have resided in the village for longer and whose homes and farmland are located at lower altitudes, lost their homes more than younger people. Nevertheless, we can still achieve the baseline balance for the age variable if we focus on the age range of 40–70 years in 2000. Using this trimmed sample is also justified because this cohort corresponds to the working age population in 1985, as noted above, which is unlikely to be affected by shifts in generation within 15 years.

2 Estimation Results

Table 2 and Table 3 report the estimation results for the first stage (1985–2000) and second stage (2000–2010), respectively. The first-stage estimation is based on a linear probability model for the binary decision of whether a household ever adopted FNA between 1985 and 2000 or not. As reported in Table 2, we estimate three specifications.

[8]Since there are only two villages, even when adjusting by using standard clustering or heteroscedasticity robust standard errors, hypothesis tests generally overreject the null (Cameron and Miller, 2015). Since our purpose is to validate the randomization of the displacement by testing the null hypothesis of a baseline balance, the overrejection of the null does not bias our interpretation.

Table 1. BASELINE BALANCE

Dependent Variable	Treatment	Control	Difference	Obs.
Years of education in 2000	7.275	7.851	-0.576	399
	[2.750]	[3.033]	(0.662)	
Age in 2000	57.240	45.694	11.546	396
	[12.629]	[13.301]	(0.662)	
Age (40-70) in 2000	55.091	52.300	2.790	256
	[10.282]	[8.963]	(0.640)	
Household size in 1985	3.460	3.032	0.428	396
	[1.328]	[1.254]	(0.134)	
Household size (Male) in 1985	2.000	1.497	0.503	396
	[1.030]	[0.817]	(0.164)	
Household size (Female) in 1985	1.460	1.462	-0.002	396
	[0.734]	[0.746]	(0.013)	
Household size (Working age) in 1985	1.920	1.616	0.304	396
	[0.566]	[0.776]	(0.076)	
Household size (Child) in 1985	1.440	1.379	0.061	396
	[1.296]	[1.065]	(0.177)	
Number of success in 1985	3.667	3.750	-0.083	399
	[9.820]	[7.780]	(0.513)	

[a]: Treatment group: those who lost all of the land and/or house due to the dam construction.
[b]: Standard errors are clustered by village.

The simplest specification is shown in column (1), and the other two specifications address the unbalanced age variable at baseline, controlling for the age variable (column (2)), and the sample trimmed to 40–70-year-olds (column (3)), which shows the baseline balance. Table 2 (columns (3)), indicates a negative and significance coefficient of land loss ($p < 0.1$) and land ownership ($p < 0.05$).

In all three specifications, the estimated coefficients of the three variables of "Displacement" ($p < 0.1$ in columns (1) and (2), $p < 0.05$ in column (3)), "known number of successful FNA owners" ($p < 0.01$), and "high discounting (dummy) in 2000" ($p < 0.01$ in columns (1) and (2), $p < 0.1$ in column (3)) are statistically significant. These estimation results indicate that, first, households that lost all their farmland and/or their entire home are more likely to adopt FNA (a 15.4–25.7% higher probability) between 1985 and 2000. This suggests the success of the social safeguard program in converting affected households into fish farmers, at least partially. However, a rather low rate of compliance may be seen as the remaining bottleneck to adopting FNA, such as the lack of initial capital (Nakayama et al., 2000). Second, households who know more successful FNA investors are more likely to adopt FNA. According to the point estimates, knowing one additional successful owner increases the probability of FNA adoption by 1.3–1.4

Table 2. FIRST-STAGE TECHNOLOGY ADOPTION DECISION, 1985-2000

	(1) Full Sample	(2) Full Sample	(3) $40 \leq \text{Age} \leq 70$
Displacement (dummy)	0.154	0.172	0.257
	(0.088)	(0.092)	(0.102)
Land loss (dummy)	-0.020	0.000	-0.283
	(0.040)	(0.000)	(0.148)
Land owner (dummy)	0.003	0.011	-0.030
	(0.003)	(0.015)	(0.067)
Number of success in 1985	0.013	0.013	0.014
	(0.002)	(0.002)	(0.003)
Risk aversion in 2000	0.010	0.011	0.023
	(0.023)	(0.023)	(0.031)
Hyperbolistic discounting in 2000	-0.005	-0.017	0.013
	(0.079)	(0.079)	(0.111)
High discounting in 2000	-0.156	-0.162	-0.125
	(0.051)	(0.051)	(0.065)
Years of education	0.053	0.055	0.054
	(0.031)	(0.030)	(0.042)
Years of education squared	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)
Household size in 2000	0.032	-0.026	0.006
	(0.050)	(0.012)	(0.017)
Head's age		-0.026	
		(0.012)	
Head's age squared		0.000	
		(0.000)	
Adjusted R^2	0.065	0.081	0.068
Observations	399	399	256

[a]: Controls: area of farmland, squared area of farmland, and village dummy.

percentage points ($p < 0.01$). This indicates that social networks play a significant role in facilitating FNA adoption. Third, impatient individuals are hesitant to adopt FNA, which is plausible because fish farming generally requires initial capital investment as well as intensive labor inputs. These requirements would lengthen the subjectively accessed gestation period for FNA investment, thereby preventing individuals with high subjective discount rates from investing. Since younger household heads also tend to invest in FNA, an individual's investment horizon may affect FNA adoption decisions. Finally, the years of education and its squared variables indicate that the overall impact of education is positive if a person has less than 13 to 14 years of schooling. This means that, for most respondents, human capital facilitates technology adoption in the initial stage.

Table 3 presents the estimation results of the second-stage technology adoption from 2000 to 2010. The estimation results of the second-stage technology adoption show contrasting tendencies among non-investors in the first stage. The right-hand columns num-

Table 3. SECOND-STAGE TECHNOLOGY ADOPTION, 2000-2010

	(1) Full Sample		(2) Full Sample		(3) $40 \leq$ Age ≤ 70	
Decision at First Phase	$D_1 = 1$	$D_1 = 0$	$D_1 = 1$	$D_1 = 0$	$D_1 = 1$	$D_1 = 0$
Displacement (dummy)	0.168	0.052	0.217	0.097	0.281	0.213
	(0.103)	(0.214)	(0.113)	(0.237)	(0.127)	(0.343)
Land loss (dummy)	0.003	-0.199	0.033	-0.211	-0.038	-0.358
	(0.181)	(0.206)	(0.178)	(0.231)	(0.221)	(0.333)
Land owner (dummy)	0.073	-0.067	0.099	-0.048	0.117	-0.043
	(0.065)	(0.061)	(0.067)	(0.062)	(0.081)	(0.078)
Number of success in 2000	0.022	-0.004	0.019	-0.004	0.021	0.002
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Risk aversion in 2010	-0.068	-0.011	-0.071	-0.016	-0.130	-0.024
	(0.036)	(0.029)	(0.035)	(0.029)	(0.043)	(0.035)
Hyperbolistic discounting in 2010	0.145	0.021	0.160	0.005	0.343	-0.072
	(0.093)	(0.083)	(0.090)	(0.085)	(0.117)	(0.072)
High discounting in 2010	0.015	0.070	0.059	0.065	0.174	0.024
	(0.075)	(0.055)	(0.072)	(0.054)	(0.093)	(0.071)
Years of education	-0.048	0.007	-0.063	0.005	-0.093	-0.029
	(0.044)	(0.030)	(0.049)	(0.029)	(0.074)	(0.042)
Years of education squared	0.003	-0.000	0.004	-0.000	0.006	0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Head's age			-0.037	-0.004		
			(0.016)	(0.019)		
Head's age squared			0.000	0.000		
			(0.000)	(0.000)		
Adjusted R^2	0.249		0.276		0.234	
Observations	399		399		256	
(Observations conditional on the first-phase decision)	(254)	(145)	(254)	(145)	(157)	(99)

[a]: The procedure was bootstraped 1000 times.
[b]: Controls: size of farmland, squared size of farmland, and village dummy.

bered (1), (2), and (3) in Table 3 report the estimated coefficients. In these specifications, none of the coefficients are statistically significant. This suggests that 15 years after the new technology was introduced, it became standardized and no longer required any specific abilities, skills, or resources to adopt it.

The first, third, and fifth columns for $D_1 = 1$ respectively show 1) second-stage FNA investment decisions conditional on the first-stage investment for the entire sample without the age variables, 2) the entire sample with the age variables, and 3) the age-trimmed sample. Based on the results of these specifications, we derive the following four findings. First, those households that lost their entire land and/or homes tended to continue to invest in FNA ($p < 0.1$ in column (2), $p < 0.05$ in column (3)). This finding suggests that the social safeguard program has permanently transformed occupations, at least for a subset of resettled households. Second, those who have higher risk aversion parameters (i.e., more risk-averse households) are more likely to exit FNA than risk-tolerant individuals in the second stage. This may be driven by the perceived uncertainty of the FNA business owing to the large number of entries and resulting decline in profitability. Third, in all three specifications, the variable "known number of successful FNA owners" continues to have positive and statistically significant coefficients ($p < 0.01$): individuals who know more successful FNA owners in 2000 tend to continue the FNA business for another decade. This implies that social learning and spillover effects persist for over 25 years. Finally, hyperbolic discounters are more likely to continue aquaculture once they have adopted FNA in the first stage. This might be because it is difficult for them to stop using such technology, even under declining profit trends, potentially leading to overfishing. This may be the main cause for "the tragedy of the commons" phenomenon in aquaculture, resulting in repeated fish deaths in the Saguling reservoir.

In both the first and the second stages, the age variables show, qualitatively, the same results, with reasonable levels of statistical significance. According to our field interviews, older individuals are less likely to engage in FNA, especially after 2000 (Miyata, 2005). Some FNA owners discontinue aquaculture, probably because older respondents tend to retire and pass on their FNA cages to their children or other heirs.

3 Discussion

FNA technology was introduced as a job opportunity that uses the newly created reservoir. Because no previous large-scale FNA program had been developed in the country, villagers did not adopt the FNA technology straight away and took time to recognize its benefits. Although resettled residents were invited to attend FNA training before the dam's construction, only some villagers started FNA at the beginning. This has two probable reasons: the technology was new to them and they needed to take out loans (Costa-Pierce, 1998; Costa-Pierce and Soemarwoto, 1990). Once the initial pioneers successfully harvested a few rounds of fish and earned an income from doing so, FNA technology attracted a great deal of interest from local residents and started to grow substantially (Figure 2). Social learning contributed to this FNA adoption pattern

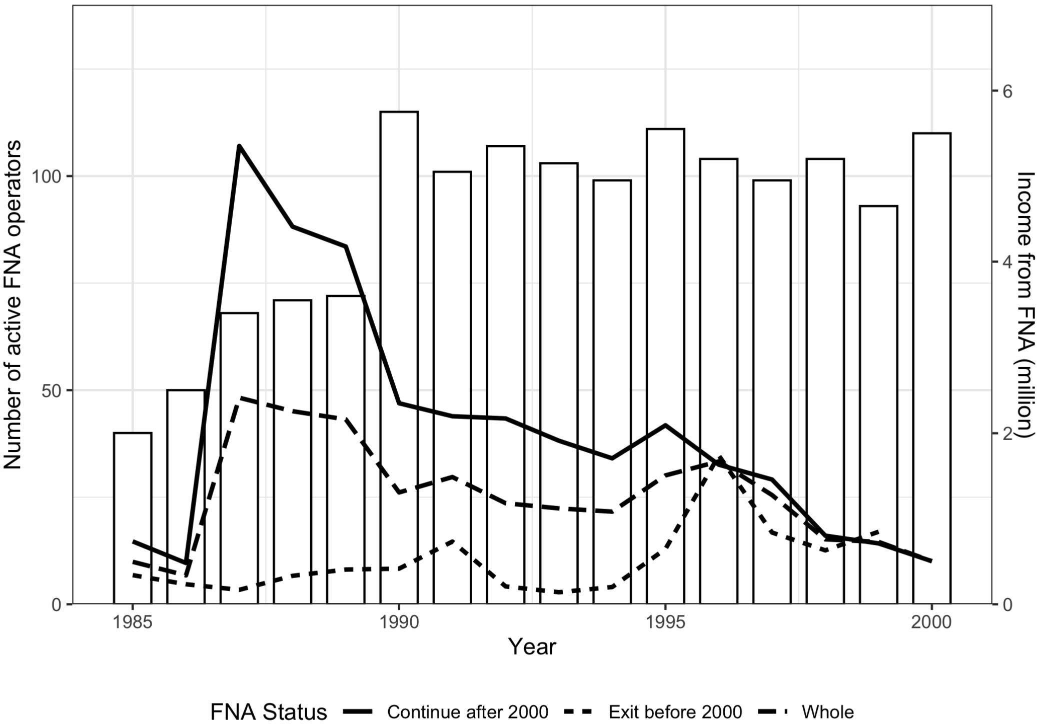

Figure 2. NUMBER OF FNA OPERATORS (BARS) AND FNA INCOME BY STATUS (LINES)
Based on retrospective FNA operation data from 1985 to 2000.

to some extent because most locals waited to see whether pioneers succeeded before deciding to adopt based on their successful experience. This observation is supported by our analysis—knowing successful FNA owners raised the adoption rate in the first stage (Table 2). Through this process, FNA grew rapidly, reaching 756 units in 1988 and 4,425 units by 1995, at the reservoir-wide level. FNA is now recognized as one of the most important income sources in the villages surrounding the reservoir.

However, the adoption process was not always smooth. In 1993, close to the point at which the number of FNA adopters peaked, the water capacity of the reservoir also reached its maximum, leading to an oxygen shortage in the water. This caused the mass death of farmed fish, generating large losses for FNA adopters. Our retrospective data show that the number of active FNA owners peaked in 1990 and gradually declined over the subsequent years (Figure 2). Owing to this sudden large-scale loss of fish, some FNA owners went bankrupt and exited the FNA business. According to our first-stage survey, between 1986 and 1996, an FNA income of those who survived these difficult times and remained in the FNA business for the first 15 years was twice as large as those who exited before 2000 (Figure 2). This experience of sudden fish losses also encouraged FNA adopters to diversify the fish species that could survive in harsh water conditions.

In addition, FNA owners could have exited in the second stage because of the lower competitiveness of FNA earnings than other emerging earnings opportunities in the area. Since fish seed and fish feed prices increased during the 1990s due to inflation, FNA income declined over time (Figure 2) and local fish farmers had to search for cheaper solutions to recover their investment costs (Miyata, 2005). Simultaneously, as the economy expanded in Indonesia, non-farming job opportunities increased and income sources shifted substantially from farming (Sudaryanto et al., 2021; Susilowati, Sudaryanto et al., 2021) to other occupations. Manufacturing plants near Cililin and Bandung, satellite cities near the Saguling reservoir, have also grown rapidly since the 1990s. People thus gradually shifted to working in non-farming jobs and this trend may have induced them to exit the FNA business (Mizuno, 1995; Miyata, 2005).

The net margin of FNA-invested households in the first stage gradually fell toward the end of the 1990s (Figure 2), and this trend of decreased FNA income over time would have caused FNA households to quit. After the sudden fish deaths in 1993, the Saguling reservoir occasionally faced similar fish losses, suggesting that the risks of FNA investment continued in later years. It was thus natural for locals to be attracted to non-farming job opportunities.

4 Conclusion

The findings of our study support the positive effect of an innovative social safeguard program in transforming and sustaining resettler livelihoods despite the controversy about whether the project benefitted all resettled people, especially the poor (Nakayama et al., 2000). Indeed, such a program has become a key component in the development projects carried out by international organizations (World Bank, 2017). If this type of a social safeguard policy following environmental and social framework does not protect the lives and jobs of project-affected individuals), such projects will be rejected by governments and international development agencies. Considering the increasing importance of hydropower in the transition to renewable energy sources, this innovative resettlement program under a dam construction project will provide critical policy insights to make such projects sustainable.

There are a few remaining caveats to our study. For example, owing to the limitations of our dataset, we abstract our analysis from certain critical determinants of technology adoption, such as factor and output prices, profits, and other market conditions. These issues warrant further investigation.

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Appendix

A Questionnaire for measuring discount factor

For the 2000 survey, we follow Pender (1996) by computing two monthly subjective discount rates based on a short-horizon experiment over seven months (A1) and a long-horizon experiment over 12 months (A2).

(A1) In each row, what do you prefer? 50 kg of rice this month or [XX] kg of rice seven months later:

(1) a. 50 kg in March 2000 or b. 45 kg in October 2000

(2) a. 50 kg in March 2000 or b. 50 kg in October 2000

(3) a. 50 kg in March 2000 or b. 55 kg in October 2000

(4) a. 50 kg in March 2000 or b. 60 kg in October 2000

(5) a. 50 kg in March 2000 or b. 70 kg in October 2000

(6) a. 50 kg in March 2000 or b. 80 kg in October 2000

(7) a. 50 kg in March 2000 or b. 100 kg in October 2000

(A2) In each row, what do you prefer? 50 kg of rice this month or [XX] kg of rice (one year from now):

(1) a. 50 kg in March 2000 or b. 45 kg in March 2001

(2) a. 50 kg in March 2000 or b. 50 kg in March 2001

(3) a. 50 kg in March 2000 or b. 70 kg in March 2001

(4) a. 50 kg in March 2000 or b. 100 kg in March 2001

(5) a. 50 kg in March 2000 or b. 150 kg in March 2001

(6) a. 50 kg in March 2000 or b. 200 kg in March 2001

We determine the *high exponential discounters* by flagging individuals who selected the earlier options when answering (A1) and (A2). We then identify *hyperbolic discounters* by checking whether a respondent's monthly discount rate is higher in the short-horizon experiment (A1) than in the long-horizon experiment (A2).

For the 2010 survey, we elicit exponential and hyperbolic discounters following Ashraf, Karlan and Yin (2006). Specifically, we ask four questions:

(B1) Would you prefer to receive 1,000,000 Rp guaranteed today or 1,200,000 guaranteed in one month?
(B2) Would you prefer to receive 1,000,000 Rp guaranteed today or 1,500,000 guaranteed in one month?
(C1) Would you prefer to receive 1,000,000 Rp guaranteed in six months or 1,200,000 Rp guaranteed in seven months?
(C2) Would you prefer to receive 1,000,000 Rp guaranteed in six months or 1,500,000 Rp guaranteed in seven months?

We classify a respondent as a *high exponential discounter* if the former options are chosen, namely, "1,000,000 Rp guaranteed today" in (B1) and (B2) and "1,000,000 Rp guaranteed in six months" in (C1) and (C2).

In (B1) and (C1), the payoff difference between the two choices is 200,000 Rp, whereas the difference in (B2) and (C2) is 500,000 Rp. Therefore, if a respondent selects "1,000,000 Rp" in (B1) and "1,200,000 Rp" in (C1), they are identified as a *hyperbolic discounter.*

B Supplementary Table and Figure

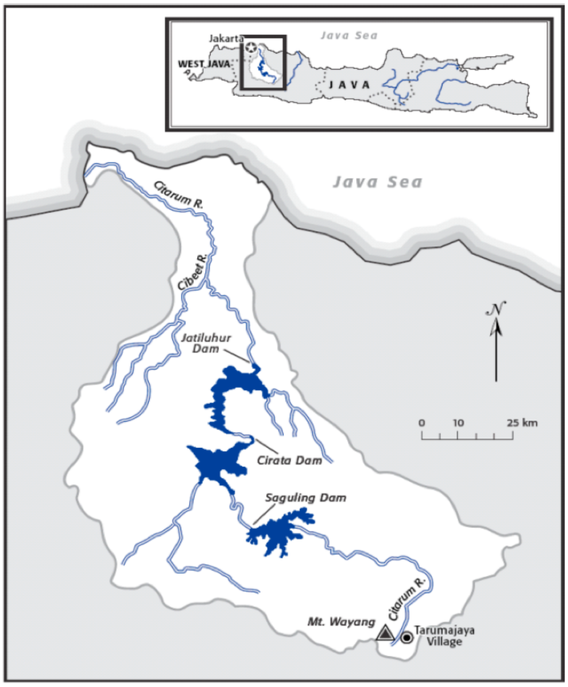

Figure B.1. MAP OF WEST JAVA AND THREE RESERVOIRS ALONG CITARUM RIVER

Source: based on Cavelle (2013)

Table B.1. SUMMARY STATISTICS

	Mean	SD	Min	Max	Observations
FN adoption in 1985-2000 (dummy)	0.637	0.482	0	1	399
FN adoption in 2000-2010 (dummy)	0.353	0.479	0	1	399
Displacement (dummy)	0.128	0.334	0	1	399
Home loss (dummy)	0.108	0.310	0	1	399
Land loss (dummy)	0.063	0.243	0	1	399
Land owner (dummy)	0.571	0.495	0	1	399
Risk aversion in 2000	0.000	1.000	-1.8	1.0	399
Risk aversion in 2010	-0.000	1.000	-1.1	1.1	399
Number of success in 1985	3.739	8.055	0	60	399
Number of success in 2000	5.699	7.165	0	41	399
Hyperbolic discounting in 2000	0.098	0.297	0	1	399
Hyperbolic discounting in 2010	0.158	0.365	0	1	399
High discounting in 2000	0.459	0.499	0	1	399
High discounting in 2010	0.629	0.484	0	1	399
Years of education in 2000	7.777	3.001	0	17	399
Head's age in 2000	47.152	13.750	20	88	396
Head's age (40-70) in 2000	52.660	9.169	40	70	256
Household size in 2000	4.642	1.829	2	13	397
Farmland in 2000	0.277	1.233	0	15	399

Source: Authors' calculation using Saguling Household Survey 2000 and 2010.