UNITED NATIONS UNIVERSITY

UNU-WIDER

World Institute for Development Economics Research

Research Paper No. 2006/104

Credit Constraints as a Barrier to Technology Adoption by the Poor

Lessons from South-Indian Small-Scale Fishery

Xavier Giné[1] and Stefan Klonner[2]

September 2006

Abstract

We study the diffusion of a capital intensive technology among a fishing community in south India and analyze the dynamics of income inequality during this process. We find that lack of asset wealth is an important predictor of delayed technology adoption. During the diffusion process, inequality follows Kuznets' well-known inverted U-shaped curve. The empirical results imply that redistributive policies favouring the poor result in accelerated economic growth and a shorter duration of sharpened inequality.

Keywords: technology adoption, inequality, fishing sector, India

JEL classification: O33, O13, O25

[1] World Bank; xgine@worldbank.org. [2] Cornell University; stefan@klonner.de.

This is a revised version of a paper originally prepared for the UNU-WIDER project conference on The Impact of Globalization on the World's Poor, directed by Professors Machiko Nissanke and Erik Thorbecke, and organized in collaboration with the Japanese International Cooperation Agency (JICA) in Tokyo, 25-26 April 2005.

UNU-WIDER gratefully acknowledges the financial contributions to its research programme by the governments of Denmark (Royal Ministry of Foreign Affairs), Finland (Ministry for Foreign Affairs), Norway (Royal Ministry of Foreign Affairs), Sweden (Swedish International Development Cooperation Agency—Sida) and the United Kingdom (Department for International Development).

ISSN 1810-2611 ISBN 92-9190-888-6 (internet version)

The Tables and Figures appear at the end of the paper.

UNU World Institute for Development Economics Research (UNU-WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

Camera-ready typescript prepared by the authors.

1 Introduction

Globalization has affected the livelihoods of fishing communities in south Asia in several ways over the past half century. In this paper we study one facet of these developments, the adoption of beach-landing fibre reinforced plastic boats (FRP) by fishing households in Tamil Nadu, India. The diffusion of this new technology, which replaces traditional artisan wooden boats, is as much a product of ongoing globalizing trends as it is a response to distortions caused by previous waves of innovation triggered by globalization.

We shed light on this process by studying both the determinants of technology adoption as well as the resulting income and inequality dynamics over the process of technology diffusion within a fishing village. The data, which was collected by the authors in 2002 and 2004, cover 65 boat-owning households of a fishing village where the first fibre boats appeared in 2001. We find, first, that poorer households adopt later while ability to operate the new technology does not significantly predict the timing of adoption. Thus inequality and lack of wealth is responsible for a socially inefficient sequence of individual adoptions, whereby the rich and not the most able fishermen adopt first. Qualitative interviews with respondents suggest that lack of wealth delays technology adoption mainly through credit constraints and, to a lesser extent, higher risk aversion among poorer households.

Second, we find that inequality during the process of technology diffusion follows Kuznets' well-known inverted U. Initially, the technological innovation widens the gap between the rich and the poor, but after the entire community has completed the technological shift, inequality drops to a lower level than before, which implies that in the long run the innovation studied here benefits the poor more than proportionally. We conduct simulations to investigate how different counterfactual distributions of initial wealth across the sample affect adoption timings. Here we find that a redistributive policy favoring the poor results in accelerated economic growth and a shorter duration of sharpened inequality, albeit the quantitative impact of such a policy is small. When we simulate the adoption process for a sample of only rich households, in contrast, the process of adoption is completed ten times as fast as observed in the actual data, implying that rich communities can enjoy the benefit from technological innovation, and thus grow, considerably faster than poor ones. These findings provide a micro illustration of Nissanke and Thorbecke's (2005) point that the relationship between globalization and poverty is complex and may be non-linear.

Among existing studies of technology adoption in low income environments, the context studied here is of particular interest because we focus on a capital intensive technology. In contrast, the bulk of existing literature has focused on divisible, comparatively inexpensive technologies, such as high yield variety seeds, the switch from food to cash crops, or use of chemical fertilizers. As a consequence, the role of wealth and initial inequality among a group of entrepreneurs for the adoption process, as well as the resulting income and inequality dynamics have deserved little attention.

The rest of this paper is organized as follows. In the next section we provide some background on globalization and India's fishing sector. Section 3 introduces the context of this study and the data. Section 4 reviews relevant existing literature on technology adoption. Section 5 sketches a theoretical framework that illustrates how wealth affects the timing of technology adoption. Section 6 develops the empirical methodology and presents results. In Section 7 we simulate the adoption process for alternative distributions of initial wealth. The final section evaluates the findings and draws conclusions.

2 Globalization and South India's Fishing Sector

To put the present study into the more general perspective of globalization and its impact on the poor, this section sketches important developments in south India's fisheries over the last 40 years with particular reference to the consequences of international development assistance and technology diffusion.

Until the 1950s the prevailing vessel on the coasts of southern Kerala and Tamil Nadu was the kattumaram, a boat which is manufactured by hand tying together a few logs of wood which are shaped by traditional carpenters. Kattumaram literally means tied-log raft (*maram* is Tamil for log while *kattu* means tied). The timber used for kattumarams is albizia, a light weight, fast-growing tropical tree found in forests throughout south India. Traditionally, kattumarams were equipped with a sail for propulsion.

South India's fisheries were hit by globalization as early as the late 1950's when European donors implemented large comprehensive development projects. The case of the Indo-Norwegian project is particularly well documented (e.g. Sandven, 1959), which called for the mechanization of fishing boats, provision of repair facilities, introduction of new types of fishing gear, improvement of processing methods, building of ice plants, and supply of insulated vans and motor crafts for transport of fresh fish. The most successful vessel introduced under the program was a fully mechanized 32-ft trawler with a powerful 84-90 hp inboard engine. A new trawler cost around Rs. 125,000 in 1978 prices (which equals about Rs. 600,000 in 2004) and had a crew of 15-20 members. The high cost of the gear and limited access to credit explains why the majority of trawler owners were businessmen and traders rather than genuine fishermen. Owners used to hire a captain and a crew to operate the vessel and provided incentives by entitling each of them to a share of the fish sales.

This and subsequent development projects led to a considerable change in the structure of asset ownership and labor relations in fishing communities. While family sized small scale enterprises were the dominant mode previously, productive assets were now concentrated in the hands of a few. Moreover, economies of scale made much of the labor previously employed in the fishing sector redundant and many fishermen became wage laborers on trawlers as the traditional technology was not able to compete with the new one. In consequence, while aggregate production soared, asset and income inequality increased as well (Platteau, 1984; Kurien, 1994).

The introduction of mechanized vessels, moreover, has depleted the resource base on which small as well as large scale fishing was relying by harvesting shrimp in waters close to the coastline in large quantities. In this connection, it is estimated that Tamil Nadu currently has as much as twice the number of trawlers that could be sustained by the resource base on the long run (Vivekanandan, 2002). Since the mid 1980's, these developments have increasingly threatened the livelihoods of small-scale fishermen along the coasts of south India. It should be noted in this connection that many places on the coast do not have the option to directly engage in trawler fishing because a trawler requires harbor facilities as, unlike a kattumaram, the vessel is too large to land on a beach.

The depletion of the resource base in waters adjacent to the shore, moreover, increased the pressure on small-scale fishermen to venture into deeper waters. These developments, in turn, created rising demand for engine propulsion in the form of an outboard motor (OBM), which increases the radius of operations of a kattumaram considerably. At this point, globalization enters the picture once more with India's federal government easing the until then heavily protective import policies, which led to a drop in cost of imported, internationally leading brands, such as Yamaha, Suzuki and Evinrude. It thus comes as no surprise that since the mid 1980's small OBMs of eight to nine horse powers have spread rapidly throughout south India's coasts.[1] It became common practice to mount such an engine on a kattumaram, which was previously propelled by sail and manpower only (Kurien, 1994).

Finally, in the mid 1990's fibre reinforced plastic boats entered the stage. Several factors simultaneously contributed to this development. First, the technological hybrid of kattumaram and OBM proved to be problematic as the vibrations of the engine strain and damage the substance of the vessel (Kurien, 1995). Second, the material used for FRP production became cheaper relative to the timber used for kattumaram manufacturing. On the one hand, through trade liberalization, fibre materials, which had been in use in the western hemisphere in aerospace, automotive and marine industries since the 1950's, became less costly. On the other hand, albizia became more and more scarce and expensive because of successive deforestation and other demands. Finally, blueprints for appropriate shapes of FRP boats (capable of negotiating high surf and beach landing) became available. In 1995, a boat yard near Pondicherry started out by manufacturing a boat, the so-called Maruthi boat, which resembles a vessel previously developed in Sri Lanka for similar coastal conditions as encountered in southern Tamil Nadu (Kurien, 1995). Moreover, supported by federal funds, the Tamil Nadu state government sponsored research and development of a new model particularly suited for maritime conditions of India's south-eastern coasts during the 1990's, which went into production in 2000 (Pietersz,

[1] In contrast, previous attempts of leading international OBM manufacturers to target India's small scale fishermen in the 1970's were largely unsuccessful (Pietersz, 1993).

1993; The Hindu, 2001). Both of these boat types are around 18 feet long and are operated by a crew of three to four fishermen.

The combination of FRP boat and OBM facilitates a considerably wider radius of operation than the kattumaram as well as greater carriage capacity and more convenience (The Hindu, 2001). It is also worth noting that the emergence of the beach landing FRP has left the labor-intensive character and fragmented ownership of productive assets of kattumaram fisheries unchanged. In contrast to the great societal changes triggered by the earlier development programs, FRPs thus appear to have the potential to improve individual livelihoods without turning the distribution of productive assets and the structure of labor markets upside down.

3 The Study Village

The village of study is located in the southern part of the coast of the gulf of Bengal, close to the pilgrim center of Tiruchendur. With a population of 1,500, there were 75 boats operated by 67 households in late 2003. About 250 men worked on these boats, either as owner/captain, family crew or wage laborer. The village has neither a harbor nor a jetty, a fact that restricts operations to beach-landing boats. All year-round operating vessels have a crew of two to four men and are operated by local households. All of these households belong to the exclusively catholic boat-owning community of the village, which used to belong to a specific caste before collectively converting about 400 years ago.

On a typical day, boats leave the shore around 1 am and land at the village's market place on the beach between 7 and 11 in the morning. There, local fish auctioneers market the catches to a group of buyers, which comprise local traders as well as agents of nation-wide operating fish-processing companies.

In our study village, the first FRPs were adopted in January 2001. By January 2004, 48 households were operating at least one FRP. The vast majority of FRPs is of the Maruthi type and 18 feet long by 7 feet wide, with two boats being slightly longer, measuring 21×7 feet. According to villagers, FRPs started to spread in 2001, but not earlier, because an FRP dealership opened in nearby Tiruchendur around that time, making such boats readily available. The cost of a vessel is around Rs. 70,000. All of the adopting households already owned a seven to nine horse powers OBM previously, which sells at Rs. 50,000 to 70,000. In comparison, a new kattumaram came at a cost of around Rs. 20,000 at the time of our 2004 interview.

According to fishermen and our data, with the same number of crew, an FRP's landings are about 50% bigger than those of a kattumaram. Given the yields of fibre-boat fishing, every owner of a kattumaram in the village we interviewed assured that he wanted to switch to a fibre boat as soon as possible. Fishermen repeatedly pointed out, however, that fishing on an FRP requires a different set of skills than those needed to operate a kattumaram. For that reason it is common practice among the buyers of fibre boats in the village to hire migrant laborer-fishermen from Kerala as crew members who have previously gathered experience with this technology.

Vessel financing and marketing of fish catches are interlinked for almost all boat owning households that we interviewed. Although the focus of the present study is on the adoption of FRPs, it is instructive to start out with the credit cum marketing contract common for kattumarams. For the purchase of a craft, the auctioneer gives a loan of about Rs. 15,000 and 25,000. In return, the boatowner sells all daily catches through that auctioneer, who keeps 5 percent of the value of the sales. The boatowner does not repay the principal. As a consequence, the commission comprises a compensation for the marketing services as well as an implicit interest payment on the amount owed. When a boatowner switches auctioneers, the new auctioneer settles the debt with the previous one. Switching of auctioneers does occur occasionally. The superiority of this interlinked share arrangement over separate debt and marketing contracts is likely a result of, first, limited liability of the fisherman and, second, costless monitoring of the fisherman's day-to-day success by the auctioneer. It is interesting to note that this credit cum marketing arrangement is identical to the one reported by Platteau (1984) in fishing villages in Kerala twenty years earlier.

The contract for FRP financing is similar, albeit not identical. The auctioneer advances funds for the purchase of the vessel. However, in addition to a commission of 7 percent, the auctioneer keeps another 10 percent of daily sales, which he deducts from the principal owed by the boatowner. Unlike a kattumaram owner whose level of debt remains constant, an FRP owner asks his auctioneer for additional funds from time to time. When such additional funds are granted, they bare no interest and are added to the fisherman's outstanding balance. The emergence of this feature of debt reduction and repeated renegotiation can be explained by the following two reasons. First, fibre boat fishing consumes more working capital, such as nets. To cover these costs, the owner of an FRP has to incur expenses between Rs. 5,000 and 20,000 from time to time. Second, since the FRP is a new technology, each individual's ability to operate it is not precisely known initially. Since the auctioneer's cash-flow directly depends on the fisherman's day-to-day success, however, the debt reduction component allows the auctioneer to drive down the debt level of an ex-post unsuccessful fisherman to a level at which the auctioneer's opportunity cost of capital does not exceed his commission income.[2] Many fishermen interviewed stated that the funds extended by the auctioneer initially do not suffice to cover the entire cost of the technology switch. It was, moreover, stated that bank and even money lender credit is virtually unavailable for this purpose as these lending sources do not accept a boat as collateral. Savings were, therefore, mentioned as the second most important source of funds to cover the cost of a fibre boat.

We briefly discuss the structure of labor contracts. On kattumarams, in Platteau's as well as our study village, typically at least two members (two brothers or father and son) of the family which owns the vessel sail on the boat. The rest of the crew consists of laborer-fishermen. To ensure daily availability of non-family labor, boatowners often tie laborers by advancing interest-free credit. On FRP boats, the common remuneration scheme for laborers is based on shares. Specifically, from the money which the boatowner receives from the auctioneer (that is net of commission and debt reduction), the expenses for fuel (around Rs. 200 per day on average) are deducted. The remainder is divided equally. One half goes to the boatowner. The other half is equally divided among all crew members who have sailed on the boat that day. If the boatowner sails himself, he also enjoys one of those shares.

Our data, which we collected between 2002 and 2004, cover all 65 households, which

[2]This aspect is the subject of a companion paper (Giné and Klonner, 2005).

owned and sailed on either a kattumaram or an FRP by the end of 2003.[3] We collected information on the type of vessel operated and the time of adoption of an FRP if applicable. From auctioneers, we obtained data on monthly fish sales by household since 2000. We, moreover, conducted a household survey on household demographics and asset possession. Household level data on fish sales with a kattumaram were the most difficult to collect as auctioneers did not always have records dating several years back on file. For 26 of the 65 households, however, we were able to collect those data and thus have a complete picture of sales before and after (if applicable) adoption as well as household characteristics. This set of households will be referred to as the core sample. Descriptive statistics for those households are set out in Table 1.

4 Existing Literature on Technology Adoption in Low Income Countries' Primary Sectors

Much of the literature that studies technology adoption in developing countries concludes that its pace has been rather slow. Feder et al. (1985), in their excellent review of the early literature point to factors such as credit constraints, aversion to risk and limited access to information, to explain why adoption has not been faster. Most of the work they survey uses static models to explain adoption, while the dynamic properties of adoption are left to heuristic or comparative-static arguments at best. In particular, the role of savings, which may be crucial in contexts where credit or insurance markets are imperfect, especially if the technology is indivisible, does not receive much attention.

The literature distinguishes between divisible technologies, such as high yield varieties (HYV) or new variable inputs, and indivisible technologies, such as tractors or the one we study here, FRP boats. If the technology is divisible, one can study the intensity of adoption of a given farmer as well as the aggregate intensity in a region. When the technology is indivisible, the decision at the individual level is necessarily a dichotomous

[3] Two households owned FRPs and hired a crew. In both cases, the household's head primary occupation is not fishing, for which reason we excluded them from the sample.

variable and only the aggregate intensity is still continuous. In the case of technologies that are not capital intensive, like the adoption of high yield variety (HYV) seeds, lack of credit is not seen as a major constraint. Instead, most of the more recent literature is concerned with the interaction between learning about a new technology and its diffusion. The first of these contributions is Feder and O'Mara (1982), who show that aggregate adoption at each point in time can follow a sigmoid curve. They consider a scale-neutral risky innovation with risk-neutral farmers holding prior believes about the mean yield of the new technology.

Besley and Case (1994) proceed in a similar fashion in their study of the diffusion of a new cotton variety in one of the south-Indian ICRISAT villages. In their model, planting the new variety not only affects current profits but it also generates public information on the profitability of the new versus the old variety. Therefore, there is individual as well as social learning from planting the new crop. They find that adoption occurs with delay because farmers underestimate initially the technology's profitability and because they fail to internalize the positive informational externality created by other farmers when planting the new crop. Among other findings, they conclude that wealthier farmers tend to innovate first because the informational externality is largest to them. Poor farmers adopt later as they benefit from the positive informational externality generated by rich farmers.

Foster and Rosenzweig (1995) take for granted that HYV of wheat and rice that became available during the Indian Green Revolution in the mid 1960's yield higher profits than traditional varieties. In their model, however, the profitability of HYV's is dictated by a target input model, whose optimal level has to be learned. The issue is, again, individual versus social learning in that each "trial" with the new variety generates additional information on the optimal level and this information is conveyed not only to the farmer himself, but also to the entire village (at least to some extent). In contrast to Besley and Case (1994), however, planting the new crop comes at the cost of choosing an input level that is far from the optimal, especially in earlier periods when there is little knowledge about the optimal level. Farmers find themselves playing a dynamic public good game, where each farmer has an incentive to wait because information is generated costlessly by another farmer experimenting with the new crop. As a consequence, those farmers who expect the greatest benefits from experimentation adopt first. As in Besley and Case (1994), those are the relatively wealthy farmers because they operate several plots, each of which benefits from the additional information in future cropping periods. Interestingly, their results imply that poor farmers in a community of relatively poor farmers adopt earlier than poor farmers with wealthy neighbors.

Bandiera and Rasul (2004) test for non-monotonicity of information spillovers among Mozambiquean farmers to whom a new sunflower variety was made available in 2000. They find an inverted U-shaped relationship between the amount of available information to a farmer and the probability that he adopts, suggesting that social effects on the individual adoption decision are positive when there are few adopters in the individual's information network, and negative when there are many. Differences in asset wealth are not found to impact the adoption decision, which is not surprising given that the NGO that provided the new variety in their context covered all switching costs.

Munshi's (2003) study of adoption of rice and wheat high yield varieties during the Indian Green Revolution focuses on the effect of the sensitivity of farm-specific growing conditions on the extent of social learning. He finds that for rice HYV's, which are more sensitive to unobserved farm characteristics than wheat HYV's, individual adoption decisions are less responsive to neighbors' experience. His analysis, however, does not take into account the effect of famers' wealth on their adoption decisions.

To summarize, all of these papers conclude that there is either a positive or no relationship between individual wealth and the decision to adopt a new technology. Wealth, however, is typically correlated with, or even indistinguishable from other important individual characteristics, such as farm size, education, access to credit, availability of other inputs, and access to information. Thus, a positive relationship between wealth and early adoption can be due to alternative factors, which are not disentangled by the existing empirical analysis. Policy recommendations, however, may well depend on the nature of the channel through which wealth affects adoption. In the papers focusing on learning, for example, it is generally argued that poor farmers adopt later because their valuation for information generated by initial "trials" with the new technology is lower. Thus, an information campaign about the benefits would result in more adoption. In general, however, it is not clarified, whether alternative channels might also play a role. Other potential candidates are differential risk aversion (see Binswanger et al., 1980), access to capital, or availability of labor. For example, if the technological innovation is labor intensive and wealthier households have better access to the labor market, a wealthier household may adopt earlier just because of labor market conditions. In the present study, we therefore make an attempt to thoroughly identify the channel through which wealth affects adoption decisions.

5 Individual Wealth and Technology Adoption: Theory

In this section we sketch a simple model of the propensity to adopt a new, costly technology and the role of initial wealth in this process. Given the discussion in Section 3, we assume that agents only have access to a savings technology to accumulate assets. Agents can produce with a traditional technology (kattumaram) that yields y_C or invest in a more profitable technology (fibre boat) which yields y_F in expectation. The fibre boat can be purchased at cost K. Since there is no possibility of borrowing, the investment of K must come from own resources. In line with Section 3 we may think of K as the cost of the boat net of the loan from the auctioneer and of y_t as income net of debt repayment and commissions. Agents accumulate assets in the following manner,

$$a_{t+1} = y_t - c_t + (1+r)a_t,$$

where r is the interest rate on savings, a_t is the level of assets or liquid wealth in period t, and c_t denotes consumption in period t. We assume that agents start in the first period with an endowment of assets a_0.

To keep things simple we assume that agents are risk neutral, live infinite periods and discount the future at rate $\frac{1}{1+r}$. Each period, a household decides whether to purchase the fibre boat and how much to save for the following period. More formally, a household's task is to choose the vector of next period's assets $\{a_{t+1}\}$ and the adoption date t^* to

$$\max_{\{a_{t+1}\},t^*} \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t c_t$$

$$\text{s.t} \quad a_{t+1} = y_t - c_t + (1+r)a_t - \imath\{t = t^*\}K, \quad a_{t+1} \geq 0,\, a_0 \text{ given},$$

$$y_t = \begin{cases} y_C,\ t \leq t^* \\ y_F,\ t > t^* \end{cases},\ c_t \geq 0 \text{ for all } t,$$

where $\imath\{\cdot\}$ denotes the indicator function.

The program which solves this problem depends on the relative profitability of the new versus the old technology. In particular, if

$$y_F > y_C + rK \tag{1}$$

the optimal program involves saving all income until $a_t \geq K$ and switching to the new technology in that same time period, which gives

$$t^* = \frac{\ln\left(\frac{rK+y_C}{ra_0+y_C}\right)}{\ln(1+r)},$$

$c_t = 0\ \forall t < t^*$, $c_t = y_F, \forall t \geq t^*$.

When $y_F \leq y_C + rK$, on the other hand, the optimal program involves dissaving instantly, $c_0 = y_C + a_0$, and consuming all income generated with the old technology concurrently, $c_t = y_t$ for all $t > 0$.

By differentiating the optimal adoption time t^* with respect to the different parameters of interest, it is easy to see that the higher the initial level of assets a_0, the higher the income from the kattumaram y_C, and the higher the interest rate r, the earlier the adoption time t^*. In this simple setup, t^* does not depend on y_F other than trough (1). When utility is concave, however, it can be shown that t^* is, moreover, decreasing in y_F. Finally, if several fishermen pool their savings, e.g. through a Rosca, adoption can occur earlier on average. It continues to hold, nevertheless, that a group of wealthier individuals can achieve an earlier adoption time on average.

6 Estimation

In this section, we seek to empirically identify the determinants of the timing of technology adoption. As developed in the previous section, a risk-neutral fisherman seeks to adopt the new technology as quickly as possible when he expects the technology switch to increase his income. An important explanatory variable for the adoption decision is therefore the expected change in income resulting from the technology shift. If expectations are unbiased, the ex-post change in observed income for fisherman i can be interpreted as the (most likely noisy) realization of i's expectations. We therefore first estimate the income change of each fisherman who adopted a fibre boat before the interview date and use these results in the subsequent analysis of the timing of adoption.

6.1 Estimating the Income Change from Adoption

The goal of this section is to provide estimates of the average income that a fishing household earns with the old and new technology. With the share system that exists in the village for the compensation of both laborers and the capital obtained from an auctioneer, household income is roughly proportional to monthly fish sales generated by that household. Since both catch quantities as well as daily fish prices are subject to substantial fluctuations, however, the following analysis aims at netting out the individual-specific component in how successfully each technology is operated by a given household. Moreover, we have to allow for the possibility of both individual and social learning when the new technology is used.

Learning by doing implies that individual catches trend upwards after adoption as the individual learns how to use the new technology more efficiently over time. Social learning (or learning from others), on the other hand, implies that an individual can use the expertise other individuals have acquired with the new technology to become more efficient himself. Quite generally, the latter implies that the "learning curve" of an individual, that is his success as a function of time since adoption, depends on the amount of information available at the time he adopts. More specifically, the learning curve of a later adopter is flatter as he starts out with relatively more information at the time of adoption. With monthly sales data from 43 fishermen who switched to a fibre boat before the date of the interview, a test for individual as well as social learning is thus facilitated by the regression specification

$$\log(y_{sit}) = \mu_{si} + \delta_t + \imath\{t \geq t_i^*\} \left(\gamma_1 \tau_i + \gamma_2 \tau_{ii}^2 + \beta_1 t_i^* \tau_i + \beta_2 t_i^* \tau_i^2\right) + u_{sit}, \tag{2}$$

where y_{sit} denotes monthly sales (in Rupees) of fisherman i in month t who currently operates technology s, where $s = C$ for kattumaram and $s = F$ for a fibre boat. Also consistent with the notation in the previous section, t_i^* denotes the time of adoption by individual i, and τ_i denotes time since adoption, so that $t = t_i^* + \tau_i$. μ_{si} is an individual-specific, technology-dependent fixed effect, while δ_t is a month-specific dummy that picks up aggregate fishing conditions and shocks. Finally, u_{sit} is an i.i.d. error term with $E[u_{sit}] = 0$.

This parametrization assumes that shocks affect sales generated through the old and new technology identically in a proportional sense. This is strictly true as far as price fluctuations (per kg of fish) are concerned as the price indices faced by kattumaram and fibre boat fishermen are the same. Whether it is also an appropriate assumption for weather shocks remains an open question. It is to be expected, however, that at least the sign of the shock works in the same way for both technologies.

While specification (2) does not allow for learning by fishermen who are operating the old technology, which has been used over several decades, the term $\gamma_1 \tau_i + \gamma_2 \tau_i^2$ allows for learning by doing for fibre boatowners. In that case, γ_1 is larger and γ_2 smaller than zero if learning by doing exhibits positive and decreasing marginal returns (Foster and Rosenzweig, 1995). The term $\beta_1 t_i^* \tau_i + \beta_2 t_i^* \tau_i^2$ captures the possibility of learning from others by allowing for a different shape of the learning curve for later adopters. Here time since adoption is interacted with a proxy for the amount of information available at the time of adoption by individual i, namely the time between the first adoption in the village and the adoption of individual i. With learning from others, the individual learning curve for a later adopter is flatter as he starts out with more information in hand than any adopter before him (Foster and Rosenzweig, 1995).

A test of the hypothesis of no learning by doing is thus

$$H_L : \gamma_1 = \gamma_2 = 0.$$

Analogously, a test of the hypothesis of no social learning is implemented by testing the composite hypothesis

$$H_S : \beta_1 = \beta_2 = 0.$$

The results of the estimation of Equation 2 together with F-test statistics for H_S and H_L are set out in Table 2. According to these results, the null hypotheses of no social and no individual learning are rejected, at least at the 10% level. According to the point estimates of γ_1 and γ_2, the first adopters in the village experience an increase in sales for roughly the first ten months with the new technology.[4] The estimate of β_1 on the other hand implies that the individual learning curve starts out flat for a fisherman who adopts a fibre boat 12 months after the first adoption in the village (the absolute value of $\widehat{\beta}_1$ equals roughly one twelfth of $\widehat{\gamma}_1$).

We use the insights from the previous estimation for deriving a more restrictive econometric specification, in which there is (positive) individual learning before some cutoff date and none of it afterwards. More specifically, we estimate

$$\log(y_{sit}) = \mu_{si} + \delta_t + \gamma \imath\{t \geq t_i^*\} D_i(\kappa) + u_{sit}, \tag{3}$$

where

$$D_i(\kappa) = \begin{cases} \tau_i & \text{if } t < t_0^* + \kappa \\ \max(0, t_0^* + \kappa - t_i^*) & \text{if } t \geq t_0^* + \kappa. \end{cases}$$

Here t_0 denotes the month of the first adoption in the village while κ is a cutoff month (counted from the time of the first adoption in the village), after which no increase in individual sales occurs. The shape of the D_i function can be explained simply: for fishermen who adopted no later than κ months after the first adoption in the village, D_i equals a straight line with slope one before date $t_0^* + \kappa$. From $t_0 + \kappa$ onwards, it remains at the level attained in that period.

[4] This is obtained by calculating the maximum of the parabola implied by γ_1 and γ_2, $\frac{\widehat{\gamma}_1}{2\widehat{\gamma}_2}$.

Estimation of (3) by OLS yields a point estimate of $\kappa = 5$, which implies that learning by doing occurs during roughly the first half year of using the new technology.[5] This is not surprising given that, in contrast to the duration of an agricultural cultivation cycle, fishing is a daily, and thus a high-frequency activity.[6] The full estimation results for equation 3 are set out in Table 3. The estimate of γ is positive and significantly so, suggesting an initial 11% monthly increase in sales for early adopters. The results for the individual-specific fixed effects, μ_{si}, are graphically depicted in Figure 1 for the 25 households for which we have sales data for kattumaram as well as fibre boat fishing. Each of the 25 data points has abscissa equal to $\widehat{\mu}_{Ci}$ and ordinate $\widehat{\mu}_{Fi}$. Notice that, for those fishermen who adopted before $t_0 + 5$, $\widehat{\gamma}_1 D_i(5)$ has been added to $\widehat{\mu}_{Fi}$. The diagram thus gives the long-run expected gains from technology adoption, which will also be used throughout the rest of this paper. The straight line depicts the 45° line. According to these results, three fishermen suffered a loss in sales of more than 1%, 2 experienced virtually no change (less than 1% change), while 20 enjoyed increases in average sales between 3.5 and 158%. The average change equals 40.2% with a standard deviation of 46.8%.

6.2 Determinants of the Timing of Technology Adoption

When a technology is divisible, like the adoption of new seeds in agriculture, a farmer with several plots can choose on how many of them to try the new technology. In contrast, a fishing boat is by nature an indivisible productive asset for a household. Moreover, switching technologies is expensive, while with many technologies previousl studied in agricultural contexts, a farmer can reverse the technology switch in subsequent growing cycles without incurring a cost from switching back. To summarize, in the context of

[5] Notice that the statistical properties of the point estimate of κ are non-standard as minimization of the sum of squares over κ is a discrete problem. Therefore Table 3 only contains the point estimate of κ.

[6] The estimte of κ can be reconciled with the estimates of equation 2, which suggest that learning by doing lasts for twice as long. Notice that the quadratic function used there is downward sloping for high values of τ_i and thus leads to an upward biased estimate of the duration of learning if the learning curve is in fact flat for high values of τ_i.

adoption of new crop varieties in agriculture, the adoption decision is typically both divisible and reversible, while in the present setup, neither of these two properties holds.

Since adoption in the context of this study can be interpreted as a one-time transition from one state, kattumaram fishing, to another state, fibre boat fishing, the timing of the individual adoption decision is most suitably modelled using methods from the statistical analysis of survival data. For the estimation, we adopt the common proportional hazard assumption. According to it, the hazard λ, that is the probability that i adopts within the next period given that he has not adopted yet, can be factored into a baseline hazard function, which is the same for all individuals in the population, and a function of individual characteristics, $\mathbf{x}_i$. Specifically, it is assumed that

$$\lambda_i(t) = \lambda_0(t) \exp(\mathbf{x}_i' \beta),$$

where β is a vector of parameters. From this structure of individual hazard, the likelihood of each observed adoption time can be derived as a function of the adoption time t_i^*, $\mathbf{x}_i$ and β. An expression for the likelihood can be obtained regardless of whether or not adoption occurred before the date of the interview. When the latter is true, the observation is treated as "censored". Using Cox's (1975) semiparametric method of partial likelihood, maximum likelihood estimates of β can be obtained numerically without making any functional form assumptions about the shape of $\lambda_0(t)$.

An individual with characteristics $\mathbf{x}_i$ has a hazard higher than the sample average if she is more likely to adopt earlier than the average of the sample because she faces a higher probability of switching at any time t' after date zero, conditional on not having switched already before t'. The sign of the relationship between an explanatory variable, x_{ik} say, and the outcome variable t_i^* thus goes the opposite way from an OLS model in which adoption time is regressed on $\mathbf{x}_i$: in the proportional hazard model, a positive value of β_k implies that an individual with a higher value of x_{ik} faces a higher probability of making the transition at any given point in time, and thus reduces the expected value of his adoption time, t_i^*. In the OLS model, in contrast, a positive value of β_k implies that an individual with a higher value of x_{ik} adopts later in expectation.

From the model of the previous section, one key explanatory variable of interest is the income gain that an individual expects from the transition. Recall that, in our simple model, an individual starts saving to finance the new technology as quickly as possible only if the expected net gain from adoption is positive. Unfortunately, the researcher does not observe individual *expected* net gain but only a measure of *realized* net gain, which can be retrieved from $\widehat{\mu}_{Fi}$ and $\widehat{\mu}_{Ci}$. We interpret realized net gain as a proxy for expected net gain. More specifically, when individual expectations are unbiased, realized net gain equals expected net gain plus a random error term which has expectation zero. Define

$$\Delta y_i = \exp(\mu_F) - \exp(\mu_C)$$

as the proxy for expected net gain in absolute terms. When Δy_i is included as a regressor in the vector $\mathbf{x}_i$, however, we potentially face the problem of a contaminated regressor for at least two reasons. First, the applicable explanatory variable is expected net gain while the variable used is a noisy realization of it. We are thus facing a problem analogous to the one of errors in variables in a linear regression model. The extent of the estimation bias induced by this problem depends of course on how accurate individual expectations are. If individuals can perfectly predict the actual income change, the use of Δy_i as explanatory variable is valid. The wider realized gains are distributed around expected gains, the more severe the bias introduced by using Δy_i.

Second, individual shocks may not be i.i.d. in each month, but rather be correlated. For example, if a fisherman falls unexpectedly sick for an extended period of time right after purchasing a fibre boat and this reduces his ability to go fishing, Δy_i underestimates his expected gains.

For both of these reasons, we will experiment with two specifications in the empirical analysis. One where Δy_i is included in the $\mathbf{x}_i$ vector without modification and one where, in the spirit of a two stage least squares model, Δy_i is first regressed on a vector of instruments and its predicted values, $\widehat{\Delta y}_i$ say, are used as explanatory variable in the subsequent regression of the timing of adoption. Indirect evidence for the "noisiness" of Δy_i is provided by the fact that our estimates of Δy_i are negative for one fifth of those households for which both kattumaram and fibre sales data are available. For these households, individual rationality seems to be violated as they adopt although they expect smaller profits from the new technology.

To illustrate how income change and adoption time are empirically related, Figure 2 plots t_i^* over Δy_i. If Δy_i is an accurate measure of expected gains, unconstrained economic efficiency dictates that all households which realize a positive income change adopt immediately while those with a negative Δy_i never adopt. When funds available to the fishing village are limited, constrained economic efficiency dictates that households which realize a positive income change adopt in decreasing order of Δy_i. While there is some negative correlation between t_i^* and Δy_i (the correlation coefficient equals -0.04), this relationship is weak and statistically insignificant.

Another set of key explanatory variables refers to the capital market conditions a household faces. Here we consider two categories, income and asset variables. Within the first one, $y_{Ci} = \exp(\mu_{Ci})$, average sales generated with the old technology, proxies a household's income stream before adoption. If the technology switch requires own funds that are not present when the new technology becomes available, a household with higher y_{Ci} will be able to accumulate the required own funds faster. A significant negative relationship between y_{Ci} and t_i^* can thus be taken as evidence for a credit constraint faced by an income-poor household. Another income variable that will be used is the number of household members who earn an income.

The second one, the value of the house at the time when the new technology became available, is an important component of the assets a household can collateralize to obtain credit. A significant negative relationship between a_{0i} and t_i^* can thus be taken as evidence for a credit constraint faced by an asset-poor household. Other variables that will be initially included are household size as well as the household head's literacy, age, both linear and squared, and years as boatowner as a measure of experience.

Table 4 gives the results of the estimation of the determinants of adoption timing.[7] Column 1 gives coefficient estimates together with asymptotic p-values for the full set of regressors, including Δy_i not instrumented.[8] At conventional significance levels, only

[7] Notice that Cox's method of partial likelihood does not identify an intercept term.

[8] For the three censored observations in the sample used for this estimation we have to impute values of Δy_i. These are obtained by regressing Δy_i of the available 23 uncensored observations for which we have both y_{Ci} and $y_{Fi} = \exp(\mu_{Fi})$ on house value, y_{Ci}, age, age squared, literacy and number of crew members who belong to the extended family, and using the estimated coefficients to generate predicted

the value of the fisherman's house is a significant determinant of the timing of fibre boat adoption. The positive sign of the coefficient means that a wealthier (in terms of assets) household is more likely to adopt the new technology earlier. Of the two variables that proxy for the income status of the household, y_{Ci} is significant at the 12% level while the number of family members who earn an income is insignificant. The same applies for household size and age. A Wald chi-square test of the hypothesis that both age coefficients are equal to zero fails to reject with a p-value of 0.58.

Column 2 gives coefficient estimates for a specification that uses predicted values of Δy_i, $\widehat{\Delta y}_i$, for the entire sample. As elaborated above, the concern addressed with this methodology is that there are reasons to believe that Δy_i is a noisy realization of the income change expected by an individual. The problem, however, is to find good instruments for Δy_i that do not affect the timing of adoption directly. The best one we could find in our data is the number of crew members employed by the head of household who belong to the extended family. It is, however, still a rather weak instrument. The only two noticeable changes with this estimation procedure are, first, that y_{Ci} is now substantially less significant and, second, that our measure of experience, years as boatowner, becomes more significant. Finally, the Wald chi-square test of the hypothesis that both age coefficients are equal to zero fails to reject with a p-value of 0.92.

Guided by the findings of specifications 1 and 2 and in regard of the fact that the sample underlying this estimation is small, we also estimate a more parsimoneous version where the four least significant explanatory variables are omitted. According to column 3 of Table 4, both asset and income poverty significantly delay adoption. Households with a greater realized income gain are likely to adopt earlier, but this relationship is significant only at a level of 0.16. As before, greater experience in kattumaram fishing induces earlier adoption.

Column 4, where the income change is instrumented, confirms these findings. As in the full specification, instrumenting mainly affects the coefficient on y_{Ci}, which ceases to be significant at conventional levels in this specification. To summarize columns 1 through 4, we find compelling evidence that asset poverty delays adoption and mixed evidence that

values of Δy_i.

income poverty does so as well. On the other hand, households that can expect a larger income change from adoption are not more likely to adopt earlier.

6.3 The Role of Wealth

We now discuss in some detail how asset wealth affects the timing of adoption. We start by considering the arguments of Besley and Case (1994) and Foster and Rosenzweig (1995) that asset wealth accelerates adoption because land-rich households enjoy higher intertemporal benefits from experimentation due to their larger scale of operation. In our sample, in contrast, each household operates exactly one boat before and after the switching of technologies, so that we can safely discard the scale argument.

Another channel we can confidently rule out is that wealthy households adopt earlier because of better access to the labor market. In the setup studied here, the same amount of labor is employed to operate the old and the new technology. Each household in our sample which adopts the new technology has operated the old technology before and thus already secured the amount of labor needed for the new technology.

What about better access of wealthier households to the new technology? Each household in the sample obtained its FRP from the nearby branch of a domestic FRP manufacturer. That branch is less than 4 kilometers away from the village and no transaction costs for transportation are incurred from the purchase. Moreover, according to villagers, there has never been a supply constraint ever since the new technology has become available in 2000. It can thus be ruled that wealth works through overcoming a supply constraint or having enhanced access to the new technology.

We next examine the relationship between initial wealth and risk-bearing attitudes. It is commonly believed that preferences for risk bearing crucially depend on a household's wealth. In particular, under the plausible assumption of decreasing absolute risk aversion (DARA), households above a certain wealth level choose to incur a given lottery with positive expected payoff while households with wealth below that level choose to stay away from it, although they would accumulate assets to later choose the lottery. Apparently, adoption of an FRP entails two forms of risk.

First, the amount of fish catches fluctuates from day to day depending on weather and maritime conditions as well as individual luck. The question, however, is whether these fluctuations are more severe with an FRP than with a kattumaram. To obtain an answer, we run the regression

$$\log(y_{sit}) = \mu_{si} + \delta_t + u_{sit}$$

separately for $s = C$ and $s = F$. The resulting root mean squared errors are 0.66 and 0.50, respectively. Thus, controlling for scale by considering the natural logarithm of sales, operating an FRP entails a smaller month-to-month risk than a kattumaram. While it may be argued that daily catches may exhibit different volatility patterns across technologies than monthly ones, it is not likely that those are particularly relevant as informal insurance arrangements seem to be prevalent in these villages. In this connection, boatowners report that they can easily obtain a short-term consumption loan from their auctioneer to compensate for a series of bad catches.

Second, as pointed out in the previous subsection, a kattumaram operating boatowner may face uncertainty about the level of average gains (net of day-to-day fluctuations) from the technology shift. This together with the DARA assumption can explain later adoption by poorer but ex-post equally successful households. This explanation competes with the remaining one of credit constraints. Since our quantitative data cannot provide a definite answer in favor of either one of the two, we will use additional, perceptional data to get a sense of the relative importance of each of the two competing hypotheses. Our survey asked each boatowner the following question: "Why did you wait (are you waiting) to switch to a FRP boat? Give the most important reason.". By far, the two most frequent answers were, first, "It required a lot of capital", and second, "I was uncertain about the benefits". Table 5 gives some statistics relating to the characteristics of the respondents by their answer to this question. The pattern we find is as follows. First, the capital requirement is mentioned roughly 50% more often than benefit uncertainty. Second, wealth among those who cite benefit uncertainty as the main reason is on average more than 25% higher than among those who mention the capital requirement first. This suggests that the capital constraint is more severe for poorer entrepreneurs, in fact to such an extent that it dominates the concern about benefit uncertainty, even though that latter concern is also of greater importance to poorer decision makers when DARA is postulated. While the difference in asset wealth across answers is on the order of 30%, this difference is not statistically significant. In that light, we do not have statistically significant, albeit economically important, evidence for the assertion that a lack of wealth affects the timing of adoption mainly through limited access to capital.

7 Simulation

The findings of the estimation suggest that asset poverty delays technology adoption. To be more precise, among two households which expect the same increase in average income from adoption, the wealthier one is more likely to adopt first. In this section, we address the policy-relevant question of how alternative distributions of wealth, as measured by house value, change the pattern of technology diffusion. We focus on the relationship between the wealth distribution, which will be affected by the different economic policies considered, and the outcome variables mean income (within the sample) and income inequality.

To conduct simulations, we first need to specify a baseline hazard function, $\lambda_0(t)$. We make the assumption of a constant baseline hazard,

$$\lambda_0(t) \equiv \lambda,$$

given the small sample we have. Moreover, we consider a situation in which each household adopts exactly at the expected value of its adoption time,

$$\widehat{t_i^*} = E[t_i^* | \mathbf{x}_i],$$

which is of course a function of $\widehat{\beta}$. With a constant baseline hazard, we obtain

$$\widehat{t_i^*} = e^{-\mathbf{x}_i' \widehat{\beta}} / \lambda.$$

Finally, the parameter λ is calibrated as follows. In our sample, three households have not adopted before the interview date. We thus choose λ such that the date of the last adoption recorded before the date of the interview matches the fourth to last adoption date in the data simulated with the actual values of $\mathbf{x}_i$.

Figure 3 plots actual and simulated mean income. Notice that actual mean income uses all y_{si} for fixed t, that is y_{Fi} (y_{Ci}) enters the average when household i has (not) adopted before date t. More formally, actual mean income is computed as

$$\frac{1}{n}\sum_{i=1}^{n}\left(\imath\{t < t_i^*\}y_{Ci} + \imath\{t \geq t_i^*\}y_{Fi}\right).$$

The formula for predicted mean income is given by the same expression, except that t_i^* is replaced by $\widehat{t_i^*}$. The predicted data is generated from the specification of Column 3 in Table 4. Without reproducing the results separately, we note that the shape of the predicted graph remains qualitatively unchanged when the instrumented version, Column 4 in Table 4, is used instead.

According to the solid line in Figure 3, there are three obvious "waves" of adoption: at the beginning, then just before one year later, and finally a little more than two years later. Notice that the solid line ends at the 36th month, the last date for which we have data. Our simulation model appears to capture satisfactorily the main features of the data, though the predicted path is smoother than the stair-shaped pattern in the actual data. According to the simulation, the last household in the sample adopts 54 months after the technology has become available. At that time, predicted average income has increased by about 39%.

Figure 4 depicts the Gini index of estimated actual incomes and the Gini as predicted by the simulation model. Notice that inequality during the adoption process exhibits the familiar inverted U shape. This reflects, first, that on average adopters experience a substantial increase in income and, second, that it is not the initially income-poor who adopt first because in that case adoption would narrow the income gap between the initially income-rich and poor. In the data, we see an increase of the Gini from 0.34 to 0.38 during the first wave of adoptions. The second wave of adoptions a year later leaves inequality virtually unchanged, while the third wave results in a drop of the Gini of about 20% to a level of 0.31, which is substantially lower than the value that prevailed before the new technology was known. All in all, while the village experiences a substantial increase in inequality over a course of two years, the availability of the new technology can hardly be criticized for its long-term impact on the village economy since, at the same time, average income increases and inequality decreases substantially.

The predicted data satisfactorily captures the main features of the data. It correctly predicts the jump in inequality induced by the first wave of adoptions. The consequences of the second and third wave, however, are less clearly distinguishable in the simulated data, because, according to the dotted line, inequality gradually decreases from the eleventh month onward. The last predicted adoption in the 54th month leads the village to a Gini of 0.285, which is sixteen percent lower than the one at date zero, where all households operate the old technology.

We now turn to the simulated policy counterfactuals. We first investigate the consequences of redistributive policies. Toward this, we assume that each household in the sample holds just the mean level of wealth observed in the data, i.e. owns a house worth Rs. 75,380. In such a scenario, the credit constraint is loosened for households whose wealth is below average and tightened for the rest. If the relationship between wealth that can be collateralized and the extent to which a household is credit-constrained is concave, we expect adoption to occur more promptly on average with such a policy in place. The results for mean income and the Gini are plotted in Figures 5 and 6, respectively. According to Figure 5, equal redistribution does in fact result in a quicker adoption process. According to the simulation, the last adoption occurs a year earlier, in the 42nd instead of the 54th month, than with the actual wealth distribution. The effect on sales over the course of the adoption process, on the other hand, is rather small. With an equal asset distribution, simulated sales never exceed predicted actual ones by more than 7 percent. Moreover, when we focus on differences between simulated and predicted actual sales of more than 3%, simulated sales never lead predicted actual ones by more than five months.

According to Figure 6, a similar picture emerges for the dynamics of inequality. While the inverted U contracts by about 20% toward the origin, the change in the general pattern of inequality as measured by the Gini can hardly be judged economically significant.

A second set of simulations investigates two extreme scenarios. The first one assumes that each household in the sample holds only the smallest observed wealth, that is each house is assumed to be worth Rs. 20,000. The second one, in contrast, assumes that each household in the sample holds the highest observed wealth, that is each house is assumed to be worth Rs. 500,000. The results for this set of simulations together with the predicted actual values are set out in Figures 7 and 8. We thus consider situations in which all households are either tightly credit-constrained or virtually do not face a credit constraint at all. The mean income and inequality paths for the first simulation very closely follow the respective paths generated from the actual asset data, which suggests that the observed income pattern accompanying the introduction of the new technology closely resembles a situation in which all households are substantially credit-constrained.

The results for the second simulation, where the credit constraint is released for the entire sample, are more striking. The dotted lines in Figures 7 and 8 suggest that with a uniformly high level of asset wealth the adoption process is completed in just five months. As a consequence, the village enjoys a substantially higher mean income for about two years by which adoptions in the simulated data lead predicted actual ones. This result suggests that a community in which households face virtually no credit constraints is able to move up the technology ladder much faster than the one investigated by this study. Similarly, only a minor spike remains of the observed pronounced inverted U shape of inequality.

8 Conclusions

This paper studies the diffusion of a new technology among south Indian fishermen, which is as much a product of ongoing globalizing trends as it is a response to distortions caused by previous waves of innovation triggered by globalization. We identify determinants of the timing of technology adoption as well as resulting income and inequality dynamics during this process. We find that lack of wealth is a key predictor for delayed adoption and that the channel through which this mechanism is effective is a credit constraint. During the diffusion process, inequality follows Kuznets' well-known inverted U-shaped curve. Simulations suggest that a redistributive policy favoring the poor results in accelerated economic growth and a shorter duration of sharpened inequality, although the quantitative impact of such a policy is small.

One advantage of this paper over other studies is that context is well understood. Thus, the specific channels in which wealth matters for adoption, credit constraints as well as higher risk aversion, are identified. We conclude, like Platteau (1984), that overall our study village experienced a success story of globalization. According to our simulations, technology diffusion for the entire sample is completed in less than five years and income gains for the initially poor are relatively larger than for the rich.

What remains unaddressed by this research are the long-run consequences for the resource base and thus future generations of fishermen due to increased efficiency in fishing. Future work will have to evaluate whether the short-term gains generated by the diffusion of fibre reinforced plastic boats are both economically and environmentally sustainable. Previous instances of globalization and subsequent resource depletion in low income countries warrant scepticism.

References

[1] Bandiera, O. and I. Rasul, 2004. Social Networks and Technology Adoption in Northern Mozambique, unpublished manuscript, London School of Economics.

[2] Besley, T. and A. Case, 1994. Diffusion as a Learning Process: Evidence from HYV Cotton, Princeton University Department of Economics Working Paper 5/94.

[3] Binswanger, H., J. Dayantha, T. Balaranaia and D. Sillers, 1980. The Impacts of Risk Aversion on Agricultural Decisions in Semi-Arid India, working paper, World Bank, Washington DC.

[4] Cox, D. R., 1975. Partial Likelihood, *Biometrika* 62, 269 - 276.

[5] Feder, G., R. E. Just and D. Zilberman, 1985. Adoption of agricultural innovations in developing countries: a survey, *Economic Development and Cultural Change* 33, 255-297.

[6] Feder, G. and G. T. O'Mara, 1982. On information and innovation diffusion: a Bayesian approach, *American Journal of Agricultural Economics* 64, 145-147.

[7] Foster, A. and M. Rosenzweig, 1995. Learning by doing and learning from others, *Journal of Political Economy* 103, 1176-1209.

[8] Giné, X. and S. Klonner, 2005. Dynamic Lending with Limited Commitment and Uncertain Borrower Types: Theory and Evidence, working paper, Cornell University Department of Economics.

[9] The Hindu, 2001. Boon for small-scale fishermen, *The Hindu*, March 22, 2001.

[10] Kurien, J., 1994. Kerala's marine fisheries development experience. In B. A. Prakash, editor, *Kerala's economy: Performance, problems, prospects*, 195-214. New Delhi: Sage.

[11] Kurien, J., 1995. Plywood boats in South India, *Appropriate Technology* 22, (2), 22-49.

[12] Munshi, K., 2003. Social Learning in a Heterogeneous Population. Technology Diffusion in the Indian Green Revolution, unpublished manuscript, Brown University.

[13] Nissanke, M. and E. Thorbecke, 2005. Channels and Policy Debate in the Globalisation-Inequality-Poverty Nexus, unpublished manuscript.

[14] Platteau, J.P., 1984. The Drive Towards Mechanization of a Small-Scale Fisheries in Kerala: A Study of the Transformation Process of Traditional Village Societies, *Development and Change* 15, 65-103.

[15] Pietersz, V. L. C., 1993. Developing and Introducing a Beachlanding Craft on the east coast of India, Bay of Bengal Programme, Madras, India.

[16] Sandven, P., 1959. The Indo-Norwegian Project in Kerala, Norwegian Foundation for Assistance to Underdeveloped Countries, Oslo.

[17] Vivekanandan, V., 2002. The Introduction And Spread Of Plywood Boats On The Lower South-West Coast Of India, Technical Report, South Indian Federation Of Fishermen Societies.

Table 1. Descriptive statistics for the core sample

	Mean	Std Dev.	Minimum	Maximum
Sample Size	26			
Value of House (in thousand Rs.)	75.38	97.74	20.00	500.00
Number of Family Members with other Income Source	2.00	1.01	1.00	5.00
Average Monthly Fish Sales before Adoption (Rs.)	22052.45	15860.84	5497.34	76017.63
Change in Monthly Sales from Adoption (Rs.)**	8419.69	10550.01	-8750.07	48339.28
Household Size	6.42	3.03	3.00	17.00
Literacy of Household Head*	0.38	0.49	0	1.00
Age of Household Head	38.46	12.12	21.00	65.00
Years as Boatowner	10.57	5.06	3.00	20.00
Adopted FRP before January 2004	0.88	0.31	0	1
Adoption month**	Jan. 2002	8.88	Jan. 2001	March 2003

* equals one if he reports that he can read or write, and zero otherwise.
** for those households that had adopted before the interview, which took place in the 62nd month.

Table 2. Estimation results for equation 2

	Parameter Estimate	Standard Error	T	p
τ_i	0.03852	0.01842	2.09	0.036
τ_i^2	-0.00187	0.00109	-1.72	0.086
$t^*_i\, \tau_i$	-0.00305	0.00131	-2.33	0.019
$t^*_i\, \tau_i^2$	0.00001	0.00004	0.14	0.885
	F	p		
Test of H_L	2.48	0.0842		
Test of H_S	4.34	0.0132		
R-Square	0.694			
No. of obs.	1471			

Notes: Coefficients for 60 monthly dummies and 30 individual-specific fixed effects for kattumaram-operating fishermen as well as 42 individual-specific fixed effects for fibre boat-operating fishermen not reproduced

Table 3. Estimation results for eq. 3

	Parameter Estimate	Standard Error	T	p
κ	5			
$D_i(5)$	0.111	0.039	2.89	0.004
R-Square	0.692			
No. of obs.	1471			

Notes: Coefficients for 60 monthly dummies and 30 individual-specific fixed effects for kattumaram-operating fishermen as well as 42 individual-specific fixed effects for fibre boat-operating fishermen not reproduced

Table 4. Determinants of the timing of adoption. Dependent variable: month of adoption

	(1)*	(2)	(3)	(4)
Value of House	0.00525	0.10697	0.00557	0.00528
	(0.070)	(0.064)	(0.022)	(0.026)
Family members with Income	-0.17937	0.00521		
	(0.777)	(0.860)		
Average Income before Adoption	0.0000429	0.06286	0.0000414	0.0000287
	(0.122)	(0.439)	(0.057)	(0.158)
Income Change from Adoption	0.0000506	0.0000187	0.0000346	-0.0000074
	(0.151)	(0.786)	(0.161)	(0.912)
Household Size	0.03444	-0.0000289		
	(0.868)	(0.760)		
Literacy of Household Head	-0.86901	-0.72087	-0.73734	-0.79233
	(0.156)	(0.246)	(0.173)	(0.138)
Age of Household Head	-0.22363	-0.02748		
	(0.311)	(0.919)		
Age Squared	0.00273	0.0004796		
	(0.298)	(0.878)		
Years as Boatowner	0.10930	0.12437	0.11890	0.14000
	(0.222)	(0.149)	(0.105)	(0.065)
Log-Likelihood	-47.9	-48.9	-48.5	-49.3
Income Change Instrumented	No	Yes**	No	Yes**
Number of Obs.	26	26	26	26
No. of Obs. Censored	3	3	3	3

* Asymptotic p-value in parentheses

** Instruments: Age, age squared, years as boatowner, number of crew members who belong to the extended family

Table 5. Wealth status by self-reported reason for delay of adoption, core sample

Answer	N	Mean	Std Dev	Minimum	Maximum
Capital Requirement	13	69.2	63.7	0	250
Benefit Uncertainty	9	95.5	152.7	20	500
Other	4				

Figure 1. Individual average profitability with fibre boat over individual average profitability with kattumaram for 25 households for which sales data is available for both kattumaram and fibre boat fishing

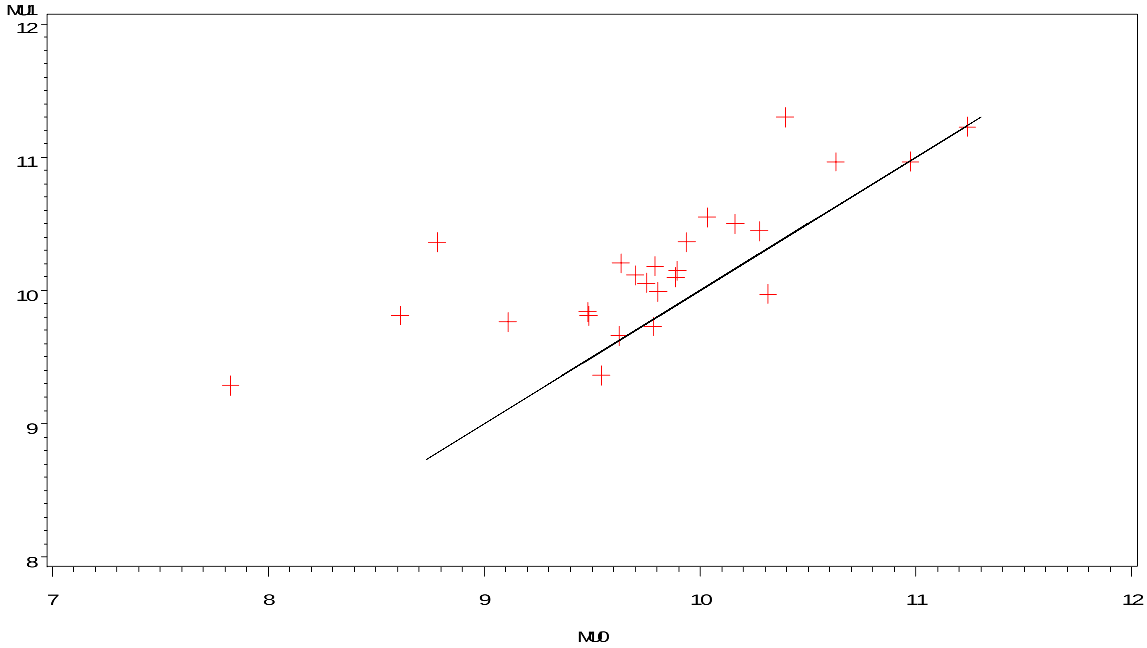

Figure 2. Adoption date over realized absolute income change for 25 households for which sales data is available for both kattumaram and fibre boat fishing

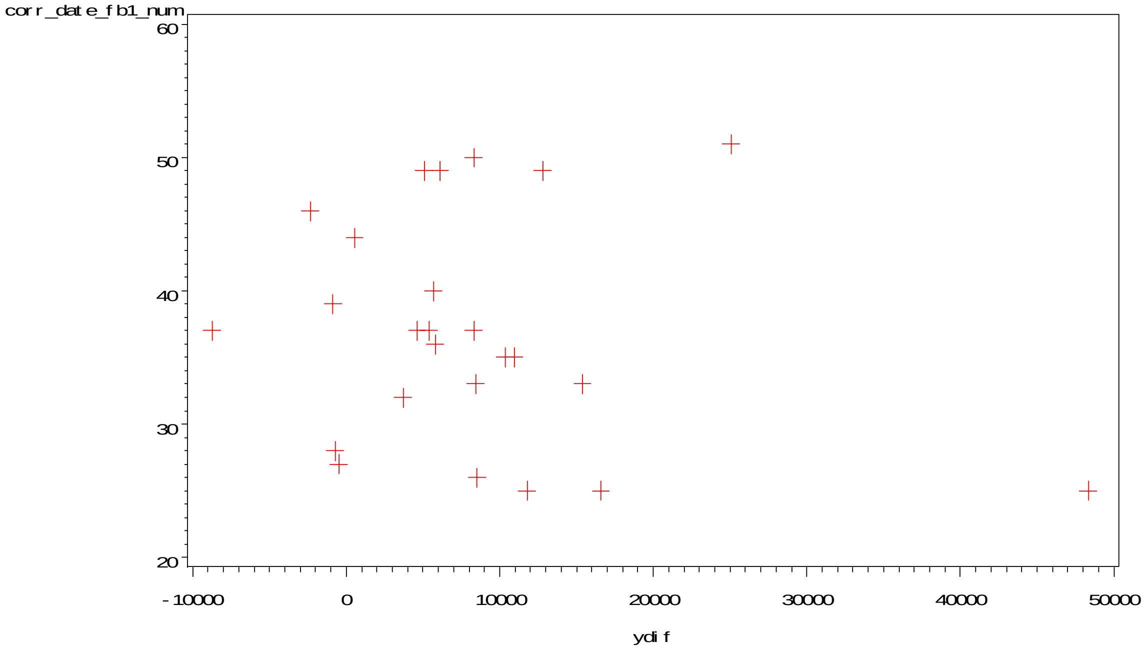

Figure 3. Mean income after the new technology became available, actual (dotted line) and predicted by the model (dashed line)

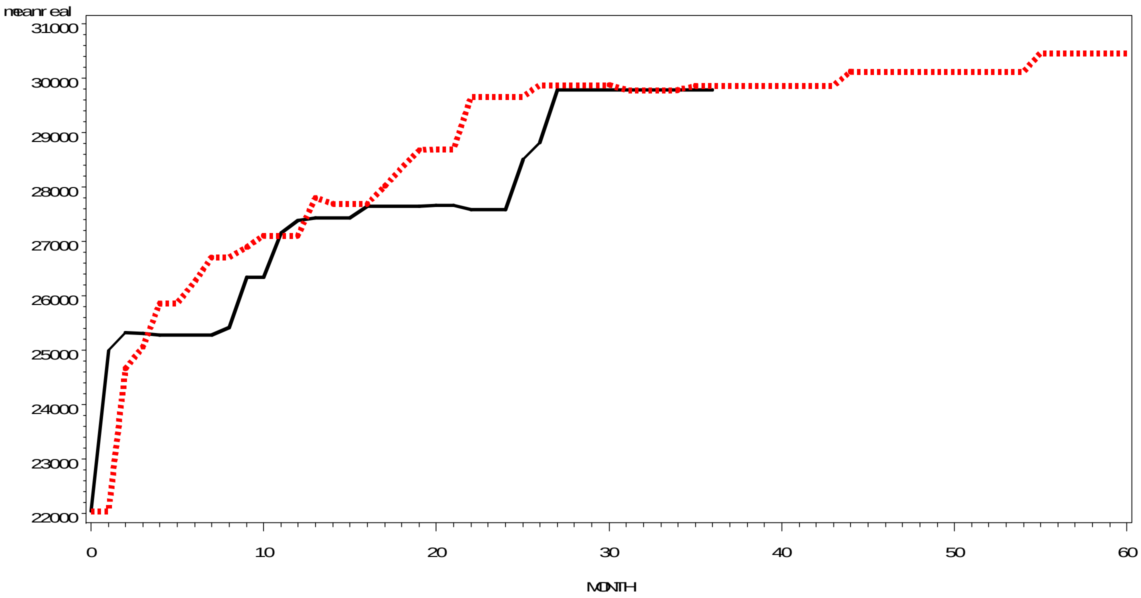

Figure 4. Income Gini after the new technology became available, actual (dotted line) and predicted by the model (dashed line)

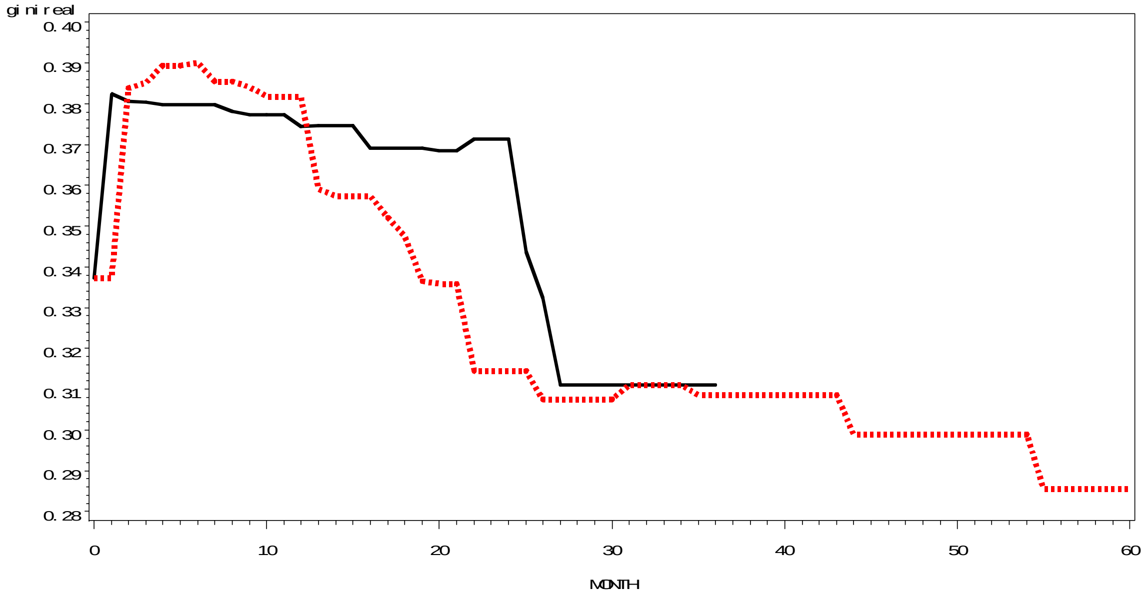

Figure 5. Predicted actual (solid) and simulated (dotted) mean income. Simulation assumes perfectly equal distribution of wealth (measured by house value) over the sample

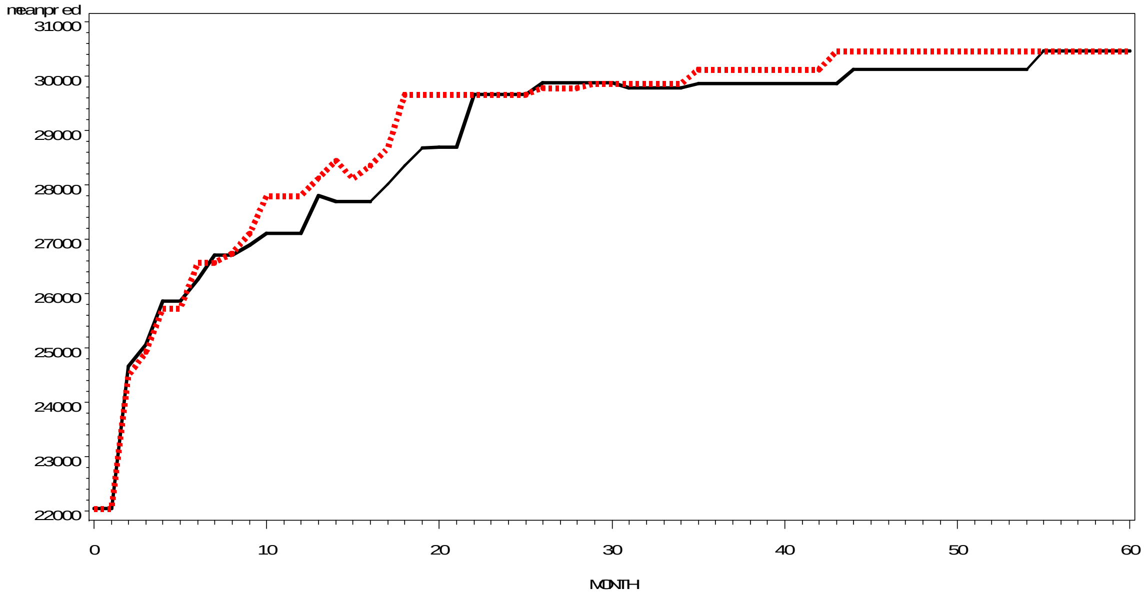

Figure 6. Predicted actual (solid) and simulated (dotted) Gini. Simulation assumes perfectly equal distribution of wealth (measured by house value) over the sample

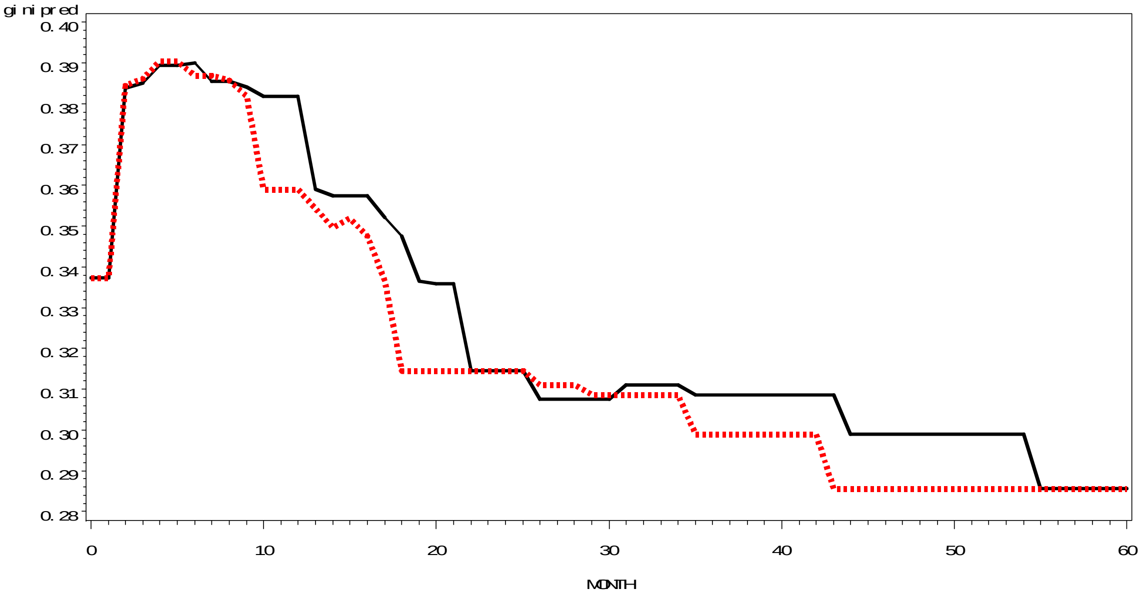

Figure 7. Predicted actual (solid) and simulated mean income. Simulation 1 (dashed) assumes the lowest observed wealth (house value equal to 20) for the entire sample, simulation 2 (dotted) assumes the highest observed wealth (house value equal to 500) for the entire sample

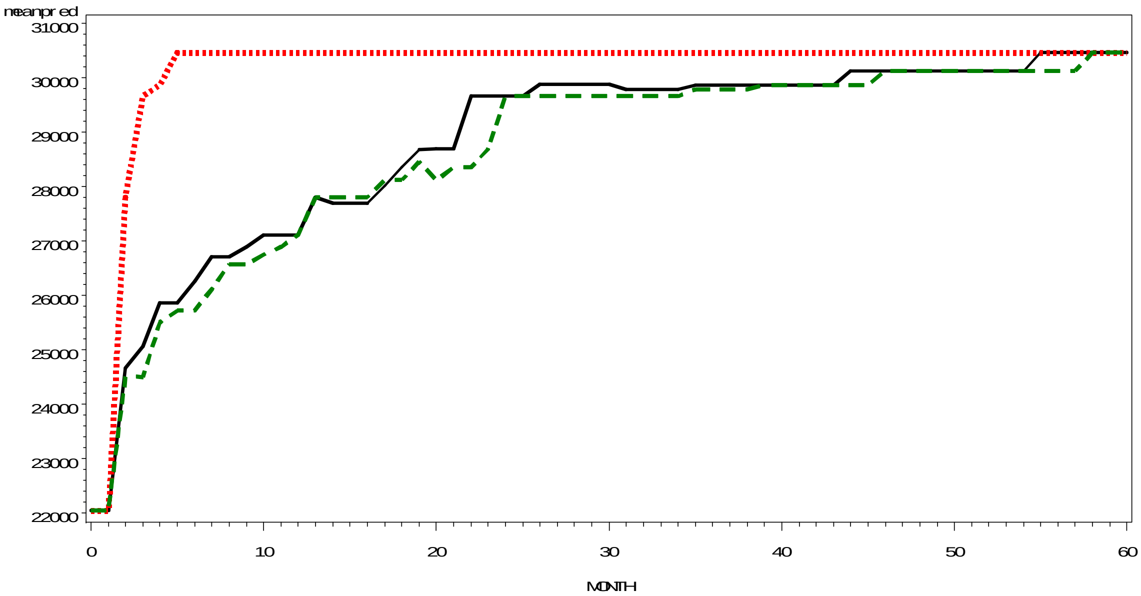

Figure 8. Predicted actual (solid) and simulated income Gini. Simulation 1 (dashed) assumes the lowest observed wealth (house value equal to 20) for the entire sample, simulation 2 (dotted) assumes the highest observed wealth (house value equal to 500) for the entire sample