Technological Change and Managerial Ability: Evidence from a Malaysian Artisanal Fishery

Ben Gilbert and Bee Hong Yeo

ABSTRACT. *Technological progress can improve economic development, but its role in the harvest of common resources has received little attention. We study the relationship between skill and the use of electronic and mechanical innovations in the productivity of Malaysian artisanal fishers. Surprisingly, electronics users do not define the frontier, and mechanical winch adopters produced well inside it. We show that if technology is a skill substitute rather than a complement, then it helps less efficient users "catch up" to the production frontier. Policy makers must balance the implications for participation rates and resource depletion against gains for the least-skilled participants.* (JEL D24, Q22)

I. INTRODUCTION

> Perhaps one of the main reasons for studying economic development is to understand better how individuals are able to make the transition out of poverty. Technology may be viewed as a means to this end.
>
> —Besley and Case (1993)

Technological change in less-developed economies has received continued attention because of its potential to improve welfare by raising output and reducing market frictions, but outcomes among small-scale common resource users have not been thoroughly studied. This paper studies the relationship between managerial ability and new technologies—cell phones, GPS, sonar, and mechanical equipment—in the production process of artisanal fishers on the east coast of peninsular Malaysia. Are the most-skilled agents better able to adopt and benefit from these technologies, or do the technologies provide less efficient firms a substitute for their deficient abilities? The canonical view of output-augmenting technical change proposed by Färe et al. (1994) is that firms producing at the frontier are the innovators who shift the frontier out, while the remaining firms attempt to catch up as new technology diffuses through the market. We propose a simple model and empirical evidence for an alternative story, with adoption more prevalent among less efficient firms.

Whether technology adoption occurs at the top or the bottom of the managerial ability distribution is important for many industries, but artisanal fisheries are particularly appropriate for studying this pattern for three main reasons, discussed in more detail below. First, there are potentially large policy and welfare implications. Millions of people worldwide rely on small-scale fisheries, but their sustainability is an increasing concern and can be jeopardized by technological changes in harvesting efficiency. Second, measuring the effect of new technology on productivity and subsequent resource dynamics may depend on a careful accounting of the adoption process. Third, there is considerable variation in ability in this sector, and the manager (the boat captain) is often both the person whose ability is most relevant for productivity, and the person who adopts and uses new technology.

This is the first study that we know of to relate adoption patterns and productivity differences to whether technology is a substitute or complement for managerial skill, and to examine the role of new technologies in the pro-

The authors are, respectively, assistant professor, Department of Economics and Finance, University of Wyoming College of Business, Laramie; and researcher, Expanse Economic Policy and Environmental Consulting, Kota Kinabalu, Sabah, Malaysia. This research was conducted while Bee Hong Yeo was a research associate at The WorldFish Center, Malaysia; she is now a cofounder of Expanse Economic Policy and Environmental Consulting.

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duction process of artisanal fishers. Cell phone use in developing economies has been shown to reduce price dispersion from search costs and increase market access and participation (Aker 2010; Muto and Yamano 2009; Overå 2006). Jensen (2007) shows that cell phones allow small-scale fishers in India to choose between coastal markets with different prices, reducing price risk, travel time, and wasted harvest. The role of cell phones and other electronics in production and harvest, however, is not clear.

We examine the intersection of skill and technology using cross-sectional data from a survey of artisanal gill net fishers on the east coast of peninsular Malaysia. We estimate the extent to which technology adopters and nonadopters differ with respect to their production efficiency, and the shape and location of their production frontiers. Stochastic frontier analysis is used to characterize skill. Boat-level information about the adoption of new technologies such as cell phones, GPS, echo locaters, sonar, and mechanical winches used to haul in fishing nets is used to estimate differences in production frontiers. Technology is not randomly assigned, and we do not claim to report a causal relationship; rather, we describe an observed relationship that is surprising and informative for policy makers. Had we found that adopters define the frontier, it would be impossible to separate a high-ability manager using a new gadget from an innovation that causes improved performance. Our finding that adopters do not necessarily define the frontier, however, suggests a more subtle relationship between technology and ability.

We present a simple model that distinguishes between technologies that are complementary to the skill endowment (and are thus "skill-augmenting") versus technologies that substitute for skill (and are thus "skill-diluting"). Note that this concept is different than "skill-biased technical change," which describes a complementary relationship between endogenous technical change and markets for one kind of labor input (high-skilled). Skill-biased technical change causes increased demand for high-skilled over low-skilled labor and can explain labor market shifts and patterns of wage inequality in some contexts (Berman, Bound, and Machin 1998). Here we are interested in the relationship between technology adoption and the managerial skill endowment. However, our approach could also be used to explain earnings inequalities between firms with different types of managers.

This relationship is important for monitoring and managing the health of small-scale fisheries worldwide. The Food and Agriculture Organization of the United Nations (FAO) estimates that the livelihoods of over 200 million people depend on small-scale fisheries, and many of these people have limited access to alternative income sources. In the sample studied in this paper, 92% of survey respondents said they do not want their children to fish, and 50% said they would change jobs themselves if they could. Among those who said they do not want to change jobs, 72% said it was because they were too old, cannot learn new skills, or do not have enough education or alternative opportunities. There are also major knowledge gaps regarding the sustainability of small-scale fisheries, but they have received increasing attention recently with expanded monitoring and research efforts by the FAO, as well as the advent of the World Small-Scale Fisheries Congress and the Too Big to Ignore initiative (FAO 2005; Too Big to Ignore 2012).

Technological change can cause unsustainable depletion of common resources; unlike agricultural improvements that raise yields and lower costs, short-run productivity gains in the exploitation of a common resource can reduce long-run resource stocks, yields, and welfare, particularly when rights of exclusion are weak or nonexistent (Gordon and Hannesson 2012; Hannesson 2007; Hannesson, Salvanes, and Squires 2010; Smith 1972; Squires and Vestergaard 2013). This "technology trap" makes it even more difficult to raise standards of living in artisanal fishing communities. Regulators in less-developed countries have limited ability to offset increases in fishing productivity by reducing effort or managing fish stocks, particularly for artisanal fisheries (Viswanathan et al. 2002). Regulators are especially limited in their ability to adjust for unobservable inputs like managerial or fishing skill, which may be augmented by the use of new technologies.

Paradoxically, equipment subsidies are often touted as a means to improve outcomes.

Certainly both types of technological change discussed here would increase aggregate extraction, although skill-augmenting changes may have a larger impact than skill-diluting. However, skill-diluting technical change may homogenize the productivity distribution, which can be helpful for things like reaching agreement on governance; but it may also increase the correlation in responses to shocks, participation decisions, congestion, and appetite for nonfishing employment in similar sectors.

Measuring the effects and trade-offs in such a technology trap requires an understanding of the adoption process in addition to an understanding of resource dynamics. For example, Kirkley et al. (2004) find (and are puzzled by) a negative coefficient on technical change from GPS use in the French Séte trawl fishery, and conclude that GPS introduction must have been correlated with an unobserved negative shock. However, it is possible that initial adopters were fishers with low navigational skill, which could lead to a negative estimated coefficient for the position of the frontier. Squires and Vestergaard (2013) take the canonical view of Färe et al. (1994) in deriving a modified steady-state harvest, resource stock, and fishing effort in the presence of technical change. However, their resulting steady-state expressions depend on rates of both technical change (frontier shifts) and technical efficiency change (rates of catching up to the frontier). These two factors can depend on whether technology is skill-augmenting or skill-diluting, which will impact both the steady state and the approach path.

The distinction between skill-diluting and skill-augmenting technical change will be important only in industries with significant variation in managerial ability or skill. We will show significant deviations from the (estimated) frontier using stochastic frontier analysis, and the literature also shows considerable skill variation in fisheries in general and in artisanal fisheries in particular. The agent responsible for this variation—the captain, who makes production decisions—is the same agent who makes technology adoption and use decisions, which may be less true in large firms with many managers and workers performing different tasks.

Skill in this context is defined as the ability to consistently catch the most fish, given observable input levels, or in other words, to produce on the production possibilities frontier (Barth 1966; Pálsson and Durrenberger 1982; Thorlindsson 1998; Viswanathan et al. 2002). Technical efficiency scores that measure firm-specific distances from an estimated frontier are often considered good proxies for skill (Squires et al. 2003; Viswanathan et al. 2002), while technological change is defined by shifts in the frontier. The literature has identified several components of fishing skill, foremost of which is the ability to find the best fishing location (Acheson 1981; Barth 1966; Marcoul and Weninger 2008). Electronic fish-finding equipment could be a complement or a substitute for this dimension of skill. Echo locaters, sonar, and GPS are obvious examples, but cell phones can also be used at sea to share information about good locations. Acheson (1981) listed knowledge of the oceanographic environment and knowledge of the species as two additional components of skill, both of which could also be complemented or substituted with electronics. To these aspects of skill, Thorlindsson (1998) added the ability to read the ecological environment, the willingness to search independently and take risks, and leadership or management qualities.

Finding the determinants of artisanal fishing skill has proven difficult, however. Pálsson and Durrenberger (1982) found no clear relationship between experience and catch. Acheson (1975) found that age and education were not strong proxies for skill. Using a stochastic production frontier, Squires et al. (1998) found that captain-specific variables were generally insignificant as predictors of technical efficiency. Viswanathan et al. (2002) and Squires et al. (2003) identify several proxies for fishery-specific knowledge in Malaysia, such as ethnicity, family size, and capital vintage, that tend to be significant even if direct measures of experience are not, but they are not all consistently significant in different fisheries.[1] Using a fixed-effects measure of technical efficiency, Squires and Kirkley (1999) found that technical efficiency was not explained by the level of production inputs. Some authors have argued that managerial (or skipper) skill is not a fixed effect, but that the frontier is defined by a handful of star performers, with performance distributed essentially randomly among the rest of the fleet (Barth 1966; Pálsson and Durrenberger 1982; Squires and Kirkley 1999; Thorlindsson 1998).

II. MODEL

Consider a firm with a decreasing returns to scale production function with scalar production inputs e purchased at a wage w. The contribution of e to output is separable from the level of technology adopted t and the level of inate ability of the firm's manager a:

$$y_i = h_i(e_i, t_i; a_i) = f_i(e_i) g_i(t_i; a_i),$$

where $g_i(t_i; a_i)$ is "effective ability" that depends on inate ability and technology. For simplicity we assume inate ability is distributed uniformly among firms as $a_i \sim U[a_L, a_H]$. Technical efficiency for firm i is defined as

$$TE_i = \frac{g(t_i; a_i)}{g_{\max}}, \qquad [1]$$

where $g_{\max}$ is defined by the firm with the highest value for $g_j(t_j; a_j)$. Technical efficiency in this model is thus also distributed uniformly as $TE_i \sim U[g_{\min}/g_{\max}, 1]$. We will consider two cases: one in which firms pay a price p to purchase a level $t \in \Re^+$ of technological investment, and one in which firms pay a fixed cost F if they adopt a discrete technology t.

We define technical change to be skill-augmenting if the distribution of technical efficiency scores is wider with a new technology than without, for example, if firms producing at or near the frontier are innovators who shift the frontier out, while nonadopters do not move relative to the new frontier without further diffusion. This would occur if the new technology is complementary with managerial skill, so that new technology augments the performance of high-ability managers more than that of low-ability managers.[2]

Definition 1. A technological input t is *skill-augmenting* if $\sigma^2_{TE}(t) > \sigma^2_{TE}(0)$ and $\mu_{TE}(t) < \mu_{TE}(0)$ for $t > 0$.

It is also possible that the new technology is a substitute for managerial skill, so that managers adopt if high-performance effort is costly to them relative to the price of technology. Russell and Alexander (1998) observe that in some developing country fisheries, innovations in electronic fish-finding and navigational equipment, as well as boat design, can substitute for traditional fishing skill, but that this has not been the case in all developing country fleets. We define technical change to be skill-diluting if the distribution of technical efficiency scores is narrower with a new technology than without, for example, if inefficient firms adopt and move closer to an existing frontier. In this case we would observe adopters toward the bottom or middle of the technical efficiency distribution.

Definition 2. A technological input t is *skill-diluting if* $\sigma^2_{TE}(t) < \sigma^2_{TE}(0)$ and $\mu_{TE}(t) > \mu_{TE}(0)$ for $t > 0$.

[1] Viswanathan et al. (2002) find that Malaysian trawlers with Chinese captains fishing in the peak season with smaller boats were significantly more efficient. Squires et al. (2003) find that in the gill net artisanal fishery on the east coast of peninsular Malaysia, more efficient vessels had newer engines, more experienced or Chinese captains, smaller vessels, larger families, and at least a primary school education. On the west coast, more efficient boats had older hulls and engines but newer nets, Chinese captains, less formal training, and larger boats with a particular brand of engine.

[2] We would also observe this pattern if more capable managers have better information about useful technological developments. In either case we would observe adopters clustered near the frontier with nonadopters lower down in the technical efficiency rankings; however, in both cases there is still some complementarity between the high skill of a manager and her ability to employ new technology.

We find empirical evidence for both skill-dilution and skill-augmentation, although skill-dilution seems more prevalent. Naturally the technical efficiency of a low-skilled firm is "augmented" if it moves closer to the frontier because of a technological adoption, but we will call this change "skill-diluting" because it is now more difficult to distinguish the skill of this firm from other efficient firms. These terms refer to the ability to distinguish between preadoption high- and low-skilled boats when technology is adopted, rather than the causal effect of the technology on individual boats. It is possible that skill-diluting and skill-augmenting effects will offset each other, leading to no observed difference in the technical efficiency of adopters and nonadopters, but rather a shifting out of the entire technical efficiency distribution. Our cross-sectional data will not allow us to distinguish the two effects empirically.[3]

We prove the following propositions in the appendix.

Proposition 1. Let the technology input be measured be a continuous variable with $t \in \Re^+$.

1. If technology is a substitute for ability, then technology is skill-diluting and firms with lower inate ability invest more in technology.
2. If technology is complementary with ability, then technology is skill-augmenting and firms with higher inate ability invest more in technology.

Proposition 2. Let $t \in \{0,1\}$ with $t = 1$ if technology is adopted and $t = 0$ otherwise.

1. If technology is a substitute for ability, then technology is skill-diluting and firms with lower inate ability are more likely to adopt technology.
2. If technology is complementary with ability, then technology is skill-augmenting and firms with higher inate ability are more likely to adopt technology.

III. EMPIRICAL APPROACH

Our empirical approach uses the location of adopters and nonadopters relative to their respective production frontiers as an informal criterion for establishing if technology is skill-augmenting or skill-diluting. We measure output-oriented technical efficiency as the distance of each firm's output from a frontier estimated using stochastic frontier analysis (Aigner, Lovell, and Schmidt 1977; Meeusen and van den Broeck 1977; Kumbhakar and Lovell 2000). Kirkley, Squires, and Strand (1995) justified using a stochastic approach in fisheries because of the inherent variability in weather, resource availability, and environmental influences. We use adoption dummy variables to capture discrete differences in the shape and location of the frontier between firms. This approach has been employed by Kirkley et al. (2004) to capture embodied technical change, that is, frontier shifts associated with specific technologies, within a stochastic frontier analysis framework.[4]

The extent to which technical change is embodied in, or disembodied from, the capital stock has been the subject of much debate in the technical change literature (Greenwood, Hercowitz, and Krusell 1997; Hall 1968; Hercowitz 1998; Hulten 1992). In this paper we directly observe the differences in equipment choice and design of capital goods and, therefore, attribute differences in the production frontier to these embodied technological differences. Kirkley et al. (2004) observe similar equipment choices for the Séte trawl fleet and

[3] Another possibility is that these technologies are ineffectual. Adopters are a small portion of our sample and may be the gullible few who took a risk on new technologies. Based on comments by respondents who adopted, we do not think this is the case. Adopters tend to indicate they think the technologies are useful at the firm level. We are not able to directly measure whether their benefits are nullified at the industry level by resource depletion and excess industry-wide effort, but we do find that adopters are not unambiguously more productive than nonadopters.

[4] The use of dummy variables to estimate technical change was established by Baltagi and Griffin (1988), who use dummies to represent discrete technical change across time periods.

find that the positive impacts of embodied technical progress were counteracted by disembodied technical regress—most likely from resource stock declines—resulting in a net decline in productivity.

Here we offer an informal criterion rather than a formal test of propositions 1 and 2 and eschew claims about technological progress or regress because of the limitations in our cross-sectional data. In order to properly identify the causal relationships between technology adoption and ability in overall productivity, we would need exogenous variation in skill and technology availability, preferably in a panel to study shifts in the production frontier and in technical efficiency within and across vessels over time. As discussed in Section IV, we have a cross section without exogenous technology variation, but the sampling design and survey protocol used to gather this data provide a highly representative and uniquely detailed sample with which to study this issue. Further, our findings rule out cases in which endogeneity would confound even qualitative interpretation, as we discuss in this and the following sections.

Using our informal criterion, skill-diluting technical change would be captured by a nonpositive difference in the location of the frontier for technology adopters relative to nonadopters (i.e., the absence of an observed frontier shift) and a tighter distribution of observations of adopters near their respective frontier than nonadopters—a higher mean and lower variance of technical efficiency. In this case, technology helps firms catch up rather than get ahead. Skill-augmenting technical change would be associated with a frontier for technology adopters located above the frontier for nonadopters (i.e., the presence of an observed frontier shift), and a wider distribution of adopter observations below their respective frontier than nonadopters—a lower mean and higher variance of technical efficiency. In this case, technology helps leading firms get further ahead. This is the case, however, in which the endogeneity of the adoption process would prevent us from disentangling the causal effect of technology on productivity from the causal effect of ability on adoption.

We estimate a stochastic translog production frontier of the form

$$\begin{aligned}\log y_i = \beta_0 &+ \sum_{j=1}^{3} \beta_j \log x_{ij} \\ &+ \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \beta_{jl} \log x_{ij} \log x_{il} \\ &+ \phi' \mathbf{D}_i + \alpha_0 I_i + \sum_{j=1}^{3} \alpha_j I_i \log x_{ij} \\ &+ \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} I_i \log x_{ij} \log x_{il} + \varepsilon_i, \end{aligned} \qquad [2]$$

where production inputs are captured by $\mathbf{x}_i$ = (labor, fuel, capital) for each boat's most recent trip, and $\mathbf{D}$ and I are frontier shifters. $\mathbf{D}$ is a vector of location and time of year dummies, and I is a technology adoption dummy variable. The data set contains several measures of capital stock, but because the small sample size limits the number of parameters we can estimate, each model is estimated three times using a different variable to capture capital stock, including net length, horsepower, and the shape of the boat, measured as the ratio of vessel width to length (as a measure of the capacity of the boat relative to its maneuverability in the water as well as the maneuverability of the crew within the vessel). In addition, these vessels exploit a multispecies fishery, but the data do not provide disaggregated catch by species. We estimate each model with total catch in kilograms as the dependent variable, and again with revenue as the dependent variable as a way of weighting the various species by their value.

In the stochastic frontier specification above, the error term is defined as

$$\varepsilon_i = v_i - u_i, \qquad [3]$$

where v and u are assumed to be distributed independently of each other and of the regressors $\mathbf{x}$, I, and $\mathbf{D}$. The first component of the error term, v, is an idiosyncratic, two-sided error term capturing exogenous shocks and is assumed to be distributed as $v_i \sim iid\, N(0, \sigma_v^2)$.

The second component of the error term, u, is a nonnegative stochastic inefficiency component drawn from a normal distribution

TABLE 1
Summary Statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
Catch (kg)	115	30	46	1	270
Typical Catch	115	54	86	0	500
Revenue (RM)	115	116	156	1	1,000
Typical Revenue	115	252	426	1	3,000
Fish Price	114	5.03	2.39	1	13
Crew Size	115	1.42	0.61	1	3
Fuel (l)	115	20	11	4	62
Net Length (m)	114	731	586	40	3,200
Horsepower	114	22	14	6	120
Boat Length (m)	115	6.21	1.71	4.15	18
Boat Width	115	1.65	0.59	0.83	6
Boat Shape	115	0.27	0.04	0.15	0.4
Trip Length (hours)	115	8.93	3.50	2	33
Any Technology	115	0.2	0.4	0	1
Net Hauler	115	0.09	0.28	0	1
Electronics	115	0.15	0.36	0	1
Number of Adoptions	115	0.42	0.94	0	5
Hauls/Trip	114	4.16	2.68	1	20
Distance (km)	115	8.35	7.54	0.5	45
Primary School	114	0.82	0.39	0	1
Secondary School	114	0.15	0.36	0	1
Share	115	0.75	0.31	0	1
Broker	115	0.50	0.50	0	1
Years Fishing	113	27	15	3	66
Household Size	111	2.61	2	0	8
Want Job Switch	115	0.49	0.50	0	1
No Other Income	114	0.46	0.50	0	1
Fishing Income	115	460	303	100	2,500
Other Income	115	325	611	0	5,000
Boat Age (years)	111	5.14	4.55	1	30
Boat Life (years left)	109	10.9	6.15	2	39
Peak Season	114	0.54	0.5	0	1
Region					
Kuantan	115	0.37	0.49	0	1
Kemaman	115	0.1	0.3	0	1
Dungun	115	0.1	0.31	0	1
Marang	115	0.17	0.37	0	1
Setiu	115	0.26	0.44	0	1
South	115	0.57	0.5	0	1

truncated at zero (Kumbhakar, Ghosh, and McGuckin 1991). This term captures differences in technical inefficiency and gives a firm-specific measure of the distance of the firm from the best practice frontier. We assume u_i is distributed $N^+(\mu_i, \sigma_u^2)$, where $\mu_i = \mathbf{Z}_i\delta$, and $\mathbf{Z}$ is a vector of firm-specific explanatory variables that account for differences in efficiency.[5]

IV. DATA

The cross-sectional data were collected as part of a direct survey of a stratified random sample of 354 licensed fishers on the east coast of peninsular Malaysia. This paper uses a subsample of 115 small-scale gasoline-powered gill net vessels. The key variables are listed in Table 1. Respondents were asked to recall their outcomes (catch, price received,

[5] One drawback to this approach is that we must assume the distribution of u_i is the same for adopters and nonadopters. We do not have enough technology users in the sample to estimate separate frontiers. However, this assumption biases against finding a difference in the mean technical efficiency between adopters and nonadopters.

and revenue) from the most recent trip as well as a "typical" trip, to state information about the production inputs and methods used on the most recent trip (crew size, fuel quantity, time spent fishing, distance traveled, frequency of casting and hauling in the net, and capital measures such as boat length and width, net length, horsepower, and the boat age and remaining usable life), to give sociodemographic household information (primary or secondary school attainment, household size, monthly income from fishing and other sources, availability of other income sources, years of fishing experience, share of the trip revenue received by the captain, and whether fish is sold to a broker), and to state whether they would like to switch occupations if they could. Detailed information about the technologies used include the presence of a net hauler, cell phone, GPS, echo sounder, and radio and/or sonar device. For the purposes of this analysis, electronic equipment was aggregated into a single presence/absence dummy variable, but the total number of new technologies used on a boat is also included in the inefficiency function as part of the $\mathbf{Z}$ vector in some specifications.

The self-reported peak season varies because this is a multispecies fishery; respondents target different species, and their outside opportunities and reliance on the fishery are heterogeneous. The Peak Season variable describes whether or not the most recent trip occurred during the self-reported peak season, or during the self-reported "lean" fishing season. "Region" lists the districts from south to north, along with a dummy variable for the southernmost three districts. Adopters are concentrated in the southernmost region.

The sampling procedures and survey instrument were designed, pretested, and administered as part of a unique collaboration between the Malaysian Department of Fisheries, the Turtle and Marine Ecosystem Centre, World Wildlife Fund–Malaysia, National Oceanic and Atmospheric Administration–Fisheries, the Department of Economics at the University of California–San Diego, and The WorldFish Center. Sampling of artisanal drift gill net vessels was stratified by villages located near sea turtle nesting sites on the east coast of peninsular Malaysia, resulting in a sample of 186 drift gill net vessels or 53% of all licensed fishers in this category, based on 2004 statistics from Malaysian Department of Fisheries district offices. The authors removed 66 diesel-powered vessels to focus on a subsample of 120 small-scale gasoline-powered vessels. Diesel-powered vessels were dropped because their production function has very different parameters than gasoline-powered vessels and must be estimated separately, yet diesel vessels did not have enough technology adopters for the analysis in this paper to be conducted. Of the 120 remaining gasoline-powered vessels, five observations were dropped for reporting implausible values for catch and inputs. The resulting 115-vessel sample represents 18 villages spaced roughly 5 to 10 miles apart, spanning five districts within two states, Pahang and Terengganu. These vessels were licensed to fish in an inshore zone within 5 nautical miles of land. Surveys were administered between September 2005 and March 2006. Details about survey instrument design and sampling protocols have been presented by Yeo et al. (2007).

Fisher Characteristics and Patterns of Technology Adoption

While our purpose is to compare technical efficiency estimates by technology category, it is informative to compare observable characteristics of adopter categories as well. Table 2 compares unconditional means by adoption status for the two technology types of interest: net haulers and electronics. First, note that catch and revenue are larger than the fleet average for both adopter categories, but the difference is significant and much larger for electronics users. However, all the input differences are much larger and more often significant for net hauler adopters, suggesting that net hauler adopters are less efficient at least relative to electronics adopters. This observation is consistent with our findings on technical efficiency, discussed in the next section.[6] Second, note that electronics users were

[6] It's also worth noting that the maximum catch and revenue were lower among technology adopters than nonadopters even though the means were higher, which supports the skill-diluting technical change story.

TABLE 2
Comparison of Means by Adoption Status

	Electronics		Net Haulers	
	$\mu(1) - \mu(0)$	t-Stat.	$\mu(1) - \mu(0)$	t-Stat.
Catch (kg)	42	3.65	17.7	1.16
Revenue (RM)	172	4.56	90.2	1.77
Crew Size	0.34	2.16	0.75	3.96
Fuel (l)	7.36	2.54	15.4	4.47
Net Length (m)	221	1.40	479	2.53
Horsepower	13.8	3.84	18.6	4.14
Boat Width (m)	0.26	1.73	0.40	2.08
Distance (km)	0.14	0.07	3.66	1.48
Primary School	−0.09	−0.74	−0.07	−0.46
Secondary School	0.31	3.43	0.17	1.40
Years Fishing	−7.93	−2.06	5	1.02
Want Job Switch	0.25	1.98	−0.32	−1.97
Boat Life (years left)	0.59	0.35	5.89	2.99

significantly more educated, less experienced in fishing (thus probably younger), and more likely to express a willingness to change occupations than the fleet average, and these relationships are either insignificant or opposite for net hauler adopters.

Although net hauler users seem less successful and less satisfied with fishing, they have made significantly larger than average investments in the occupation, as shown by the difference in remaining boat life as well as the differences in experience and other capital measures, suggesting that a net hauler is associated with a captain having a longer expected time horizon for fishery participation. Most net hauler adopters have used only 20% to 40% of their boat's life. While most electronics are relatively inexpensive—particularly cell phones—the net hauler itself is a capital investment on par with a new net or boat; the average net hauler cost among respondents was RM 3,000, while the average boat and net costs were RM 5,750 and RM,1,200, respectively. These captains may be better able to finance and amortize these expenditures, in particular if they live in the southern villages that are closer to larger markets in Kuala Lumpur.

Net haulers have been adopted more recently than electronics, with most adopted between 2003 and 2005 (the year of the survey), whereas electronics—mostly cell phones—began to be adopted in 2000. Rapid urban economic growth and increasing labor demand in nonfishery sectors in Malaysia at that time may have made adoption of an expensive labor-saving innovation more attractive for captains losing their crew in the years directly preceding the survey. We would therefore expect the effect of net hauler adoption on productivity to be labor biased. Net haulers may replace or augment labor inputs that have become more expensive, without necessarily increasing output. However, firms with lower labor productivity may also have an incentive to adopt if the net hauler will increase output by more than an additional worker; adoption may improve labor productivity but in a cross section, adopters could still appear less productive.

In light of this discussion of adopter characteristics, it seems that net hauler adopters have relatively recently invested or reinvested in the fishery, with higher fixed costs and a potentially longer time horizon than the average nonadopter. This profile could be consistent with two types of fishers: "high types" who remain in the industry by choice because their skill at fishing is relatively better than their next best option, and "low types," who have low skill but must remain in the industry because their outside options are even worse.

Our data provide evidence for the "low type" story. The pattern is most clear in Figures 1 and 2, which plot the log of total revenue against the log of fuel use, with each variable centered at its mean. Adopters are marked in black. It is clear that electronics

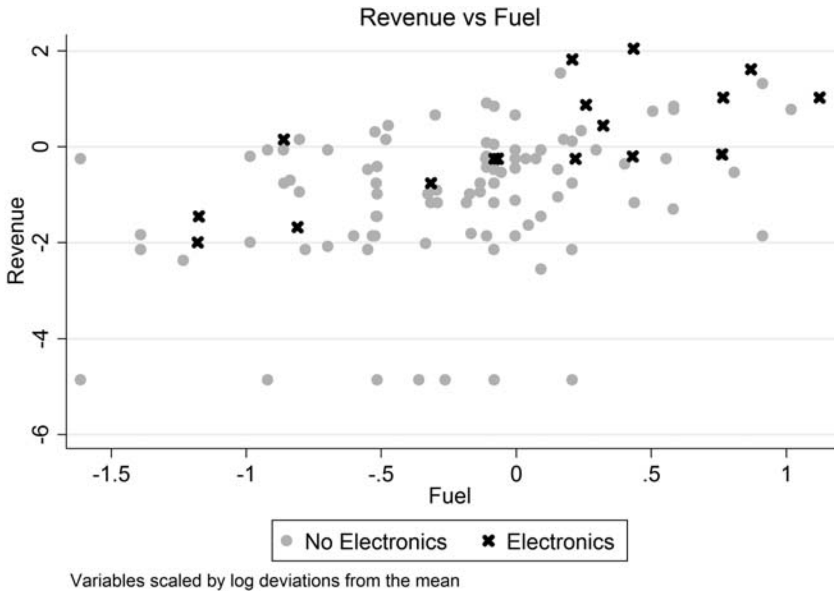

FIGURE 1
Electronics Frontier

adopters are among the upper half of the technical efficiency distribution, but they are not distinctly beyond the frontier. Conversely, Figure 2 shows net hauler adopters positioned well below the frontier at all levels of output, but for the most part they produce within a narrow technical efficiency band. Plots of outcomes against other input variables tell a similar story. These graphical results point to the skill-diluting hypothesis of technical change; for both technology types there appears to be an absence of a frontier shift and a narrower band of technical efficiency, or a higher mean and lower variance of technical efficiency for adopters. The next section will demonstrate these observations using results from the stochastic frontier analysis exercise.

V. ECONOMETRIC RESULTS

In this section we present estimates from our preferred specification of the production frontier, compare the resulting technical efficiency distributions, and show that the results are robust to alternative choices for the outcome variable and the measure of capital stock.

Parameters of the Production Frontier

We estimate three functional forms for the production environment: a translog function as described in Section III, a modified translog with quadratic terms included in $\mathbf{Z}$ instead of in the production function, and a modified Cobb-Douglas with input interaction terms and quadratic terms included only when interacted with technology dummies. The likelihood function and efficiency measures in this application are generalizations of the conventional case (Battese and Coelli 1993). Likelihood ratio tests establish that the third functional form described is most preferred:[7]

$$\log y_i = \beta_0 + \sum_{j=1}^{3} \beta_j \log x_{ij} + \phi' \mathbf{D}_i + \alpha_0 I_i + \sum_{j=1}^{3} \alpha_j I_i \log x_{ij} + \frac{1}{2} \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} I_i \log x_{ij} \log x_{il} + \varepsilon_i. \quad [4]$$

[7] Likelihood ratio test statistics are available upon request.

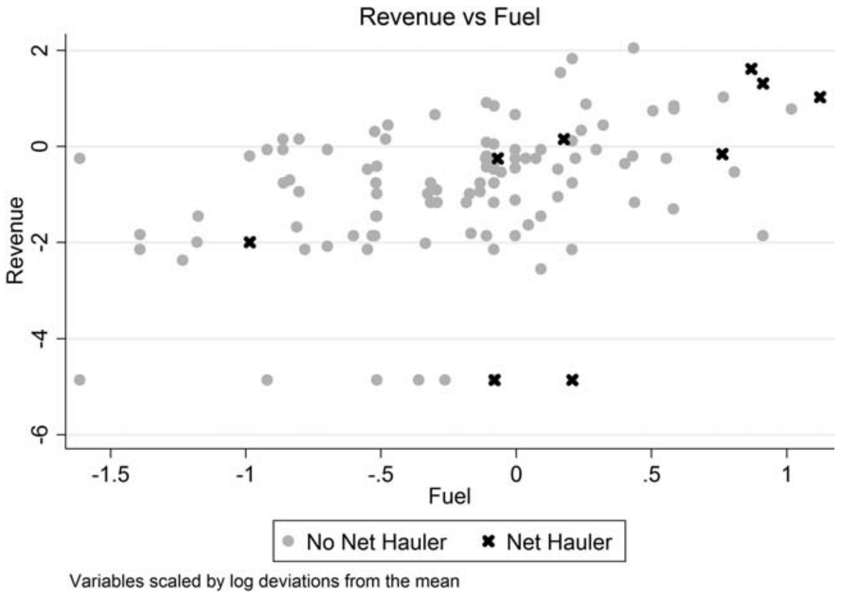

FIGURE 2
Net Hauler Frontier

TABLE 3
Production Function Parameter Estimates with Net Hauler

Dependent Variable:	Revenue			Catch		
Capital Measure	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
e(Y,K)	0.13	0.52**	1.18**	0.10	0.27	1.42**
e(Y,L)	0.21	0.03	0.26	0.31	0.23	0.31
e(Y,F)	0.49**	0.40**	0.49**	0.69**	0.68**	0.71**
Returns to Scale	0.83	0.96	1.93	1.10	1.18	2.44
Technical Change	− 1.83**	− 4.08	− 4.94**	− 2.10*	− 5.09	− 3.94**
Input Bias (K)	− 4.17**	9.62	32.37**	− 2.94	16.64	15.05
Input Bias (L)	− 6.35**	− 13.88	2.10	− 4.96**	− 7.12	− 2.17
Input Bias (F)	9.45**	0.19	− 14.38**	7.67**	− 4.09	− 8.82
Scale Bias	− 1.07	− 4.08	20.09	− 0.23	5.43	4.06

Note: I = Net Hauler.
* Significant at the 10% level; ** significant at the 5% level.

This specification was estimated separately with revenue and catch as the dependent variable and with the net length, engine horsepower, and boat shape as the capital stock measure, and results are consistent across these estimations. In all cases, continuous variables were scaled by their geometric means so that coefficients can be interpreted as elasticities. Tables 3 and 4 report estimates of output elasticities, returns to scale, technical change, and input and scale bias from technical change evaluated at the mean of inputs. Technical change from innovation is given by

$$TC_i = E(\log y_i | I=1) - E(\log y_i | I=0)$$
$$= \alpha_0 + \sum_{j=1}^{3} \alpha_j \log x_{ij} + \sum_{l=1}^{3} \sum_{j=1}^{3} \alpha_{jl} \log x_{ij} \log x_{il}, \qquad [5]$$

which is simply captured by the coefficient α_0 when evaluated at the mean. The output

TABLE 4
Production Function Parameter Estimates with Electronics

Dependent Variable: Capital Measure	Revenue			Catch		
	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
e(Y,K)	− 0.02	0.15	0.78*	0.09	0.14	0.96*
e(Y,L)	0.22	0.16	0.17	− 0.05	− 0.08	− 0.01
e(Y,F)	0.64**	0.59**	0.64**	0.66**	0.70**	0.67**
Returns to Scale	0.85	0.90	1.59	0.71	0.76	1.62
Technical Change	0.57	1.29**	1.30**	1.14*	1.15*	1.54**
Input Bias (K)	1.00	0.31	3.04	0.71	1.79	2.09
Input Bias (L)	2.78	0.80	− 0.43	1.83	0.90	− 0.31
Input Bias (F)	− 0.28	− 0.51	0.02	− 0.14	− 0.69	0.12
Scale Bias	3.50	0.60	2.63	2.40	2.00	1.90

Note: I = Electronics.
* Significant at the 10% level; ** significant at the 5% level.

elasticities with respect to particular inputs are given by

$$\xi_j = \frac{\partial \log y_i}{\partial \log x_{ij}} = \beta_j + \frac{1}{2}\sum_{l=1}^{3} \beta_{jl} \log x_{il} + \alpha_j I_i + \frac{1}{2}\sum_{l=1}^{3} \alpha_{jl} I_i \log x_{il}, \quad [6]$$

which at the mean can be simplified to $\xi_j = \beta_j + \alpha_j I_i$, with the elasticity differing by adoption status. The firm-specific input bias from technical change would be expressed as

$$IB_{ij} = E(\xi_j | I = 1) - E(\xi_j | I = 0) = \alpha_j + \frac{1}{2}\sum_{l=1}^{3} \alpha_{jl} \log x_{il}, \quad [7]$$

which is simply α_j at the mean, and the scale bias from technical change is $SB_i = \sum_{j=1}^{3} IB_{ij}$.

Consistently negative and significant coefficients of technical change for net hauler adoption shown in Table 3 suggest that less productive vessels are adopting the net haulers. Particularly, less productive labor seems to be associated with adopting net haulers; the sign of labor bias is negative in most cases and significant when the length of the net is used to measure the capital stock. The result is indeterminate for fuel and capital biases, however, because the signs flip depending on the specification. We cannot measure the degree to which adoption has improved labor or total productivity, but the negative frontier difference is consistent with a pattern of skill-diluting technical change. Likelihood ratio tests of all the technology coefficients (the α's) as a group indicate a significant difference in the frontier between adopters and non-adopters of net haulers, particularly when revenue is the dependent variable.

It is worth noting, also, that net hauler adopters were asked about their crew size before and after adoption. In our sample of gasoline-powered vessels, 3 out of the 10 net hauler adopters reduced their crew size by one person; if we include diesel-powered vessels in this count the proportion is 5 of 15, and one vessel reduced crew size by two. In other words, about one-third of artisanal drift net vessels using net haulers reduced their crew size after adopting the technology, and none of the vessels increased crew size after adoption. Furthermore, four of the vessels stated as their reason for using a net hauler that it was "difficult to find labor," six said it was "to save energy," four said it was "to make work easier," and one said "to save cost." Even after adoption, net hauler adopters had larger average labor usage (as was shown in Table 2).

The technical change coefficient for electronic equipment, on the other hand, is positive and usually significant, while the individual input biases are not significant, indicating that either more productive vessels are adopting this equipment or the equipment is improving productivity, but that electronics are

TABLE 5
Cell Phone Use Does Not Predict Higher Prices

	OLS: Fish Price
Cell Phone	− 0.005 (p-value: 0.97)
Catch	− 0.11***
Peak	− 0.11
Kuantan	− 0.02
Kemaman	− 0.05
Dungun	− 0.40**
Marang	− 0.20
Broker	− 0.13
Primary	− 0.09
Boat Length	− 0.10
Constant	2.27***
N	113
Adj. R-squared	0.16

Note: Continuous variables are measured in natural logs.
** Significant at the 5% level; *** significant at the 1% level.

not strongly substituting for any particular input. Likelihood ratio tests of all the α's as a group indicate no significant difference in the frontier as a whole. In other words the position of the frontier alone does not provide clear evidence about whether electronics are skill-diluting or skill-augmenting, although the next subsection presents some evidence for skill-dilution, using technical efficiency estimates.

Although the estimated electronics input biases are insignificant, the signs tell a sensible story: adopters generally had lower fuel productivity and higher capital and labor productivity. This would suggest that adopters are vessels that burn a lot of fuel searching for fish, with limited crew and capital endowment—more evidence of the skill-diluting theory of technical change in fisheries. This result is stronger when revenue is the dependent variable, so one concern might be that we are simply picking up the effect of cell phones, which comprise most of the electronics, being used to obtain higher prices (as in Jensen 2007). Some evidence to alleviate this concern is shown in Table 5 using a simple regression of fish prices on cell phone use and other variables. The coefficient on cell phone use is small and not significant. This result holds up across all specifications of this regression that we ran. Cell phone users in this sample are concentrated in the south; rather than contradict recent findings about cell phone use and market access, the evidence here may simply reflect geographic or social factors preventing access to alternate markets in this particular fishery. One interpretation is that cell phones in this fishery are used more for fish-finding than price finding—and in particular, for finding higher-value species—suggesting the presence of informal networks and cooperation among fishers.

Notably, fuel and capital stock are often significant explanatory variables for catch and revenue, while crew size is never significant. There is minimal variation in crew size in this sample: the minimum is one crew member and the maximum is three. It seems that fuel use, which can be interpreted as time spent searching for good fishing spots or willingness to travel to good spots, along with luck, skill, and vessel characteristics drive productivity in this fishery.

Technical Efficiency and Technology Adoption

In this subsection we provide evidence for our informal criterion of skill-diluting or skill-augmenting technical change described in Section III. Generalized likelihood ratio tests confirm the existence of a stochastic frontier and the significance of the $\mathbf{Z}$ vector in explaining inefficiency in almost all specifications we estimated. In other words, there is significant variation in measured skill, which is necessary to establish whether technical change is skill-diluting or skill-augmenting.

The stochastic frontier approach assumes technical inefficiency u_i to be uncorrelated with technology adoption, while in reality u_i and I are likely to be correlated. Skill will have different causal effects on adoption if technology is skill-augmenting or skill-diluting, and may also cause adoption if managerial skill includes the ability to find and deploy new methods before other agents. Adoption may cause changes in technical efficiency as a measure of skill if fishers differ in their ability to effectively use the technology or if the fisher was not producing on the frontier before adopting. If skill drives adoption, so that u_i causes I, random assignment of technology is required to consistently estimate causal pa-

TABLE 6
Coefficients on **Z** Variables

Innovation: Capital Measure	Net Hauler			Electronics		
	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
Hauls/Trip	− 0.33	− 0.27	− 0.25	− 0.087	− 0.14	− 0.045
	(0.277)	(0.286)	(0.246)	(0.330)	(0.358)	(0.284)
Number of Adoptions	− 1.14**	− 1.16*	− 1.18**	− 0.91	− 0.072	− 0.46
	(0.563)	(0.666)	(0.550)	(0.716)	(0.584)	(0.692)
Primary	1.28**	1.25**	1.18**	1.20*	1.41*	1.13**
	(0.588)	(0.600)	(0.490)	(0.701)	(0.839)	(0.549)
Secondary	1.01	0.83	1.10*	0.72	0.58	1.10
	(0.664)	(0.725)	(0.607)	(0.814)	(0.918)	(0.708)
Share	2.10***	2.36***	1.88***	1.58	2.02**	1.41*
	(0.812)	(0.914)	(0.670)	(1.052)	(1.022)	(0.771)
Constant	− 1.03	− 1.46	− 0.80	− 0.88	− 1.73	− 0.69
	(1.272)	(1.341)	(0.992)	(1.629)	(1.859)	(1.103)

Note: Dependent variable: Log of Revenue. Standard errors in parentheses.
* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

rameters for I.[8] Lacking random assignment, we attempt to control for this source of correlation by including variables in **Z** that capture the propensity to adopt and explain variation in u_i.

On the other hand, if adoption and use of technology causes technical efficiency, even random assignment of technology will induce correlation between u_i and I. We attempt to control for this source of correlation by including variables in **Z** that capture the propensity to make productive use of technology and explain variation in u_i (e.g., the number of technologies used and the education level). Causality is likely to run in both directions, as adoption and skill are jointly determined, and there is some overlap in **Z** that will control for both the propensity to adopt technology and the propensity to effectively use technology. Therefore, a number of models with different variables included in **Z** are tested.

The likelihood function did not converge in a few cases, so we chose several sets of explanatory variables for the inefficiency function and compared results where convergence was achieved. The distributions of technical efficiency by adopter category were consistent across these specifications. The **Z** variables reported in Table 6 include whether the respondent attended primary or secondary school, the number of times the net was hauled in on the most recent trip, the respondent's share of earnings on the most recent trip, and the number of innovations adopted by the respondent's vessel.[9] Technology adoption dummies were used in equation [4] to determine the position of the frontier, so are not included in **Z**.

Positive signs are associated with lower efficiency. Coefficients on primary school education and catch share paid to the respondent are positive and often significant. Catch shares

[8] Another argument by Zellner, Kmenta, and Dreze (1966) holds that predetermined, fixed production inputs may be thought of as exogenous when examining the most recent period of outputs. A capital investment decision (boat size, engine size, etc.) made several years ago also determines the choice of crew size and fuel use in every subsequent trip. At the point of the most recent fishing trip, these input decisions are predetermined. Thus, this argument holds that output cannot simultaneously influence input decisions. One drawback to this argument, however, is that if fixed vessel- or skipper-specific attributes are constant in the long run, such as innate skill, motivation, or ability, the same attributes that influenced the capital decision years ago may also influence this period's output.

[9] We estimated several additional specifications that mirror as closely as possible the inefficiency hypotheses tested by Viswanathan et al. (2002) and Squires et al. (2003), who found that inefficiency is influenced by vessel characteristics, fishing season, crew incentives, and human capital, although only a few of these were individually statistically significant. The additional specifications we estimated included experience, a full set of location dummies, boat width class, and season. These results are available upon request.

TABLE 7
Test for Equality of Means of Technical Efficiency by Technology Adoption

Dependent Variable: Capital Measure	Revenue			Catch		
	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
I = *Net Hauler*						
$\mu(1)$	0.72	0.73	0.74	0.73	0.73	0.73
$\mu(0)$	0.45	0.46	0.45	0.67	0.67	0.68
$\mu(1) - \mu(0)$	0.28***	0.27***	0.28***	0.05**	0.06**	0.05**
t-Statistic (p-value)	9.46 (0.00)	9.26 (0.00)	9.60 (0.00)	2.30 (0.01)	2.28 (0.02)	2.24 (0.02)
I = *Electronics*						
$\mu(1)$	0.54	0.52	0.51	0.65	0.65	0.65
$\mu(0)$	0.42	0.41	0.42	0.63	0.63	0.62
$\mu(1) - \mu(0)$	0.13**	0.11**	0.09*	0.02	0.02	0.03
t-Statistic (p-value)	2.20 (0.02)	1.84 (0.04)	1.44 (0.08)	0.69 (0.25)	0.68 (0.25)	1.24 (0.11)

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

paid to the respondent were included to capture fishing incentives, but greater shares are highly correlated with fewer crew members. Rather than capturing incentive effects, this result likely indicates that, ceteris paribus, one-man boats were less efficient. The positive sign on primary school completion may be hinting at the selection issue with fishing; skippers who completed school but could find no other job may have found fishing as a last resort, not because they are particularly skilled at it. The negative and significant coefficients on the number of technologies adopted for the net hauler specifications is picking up those vessels who also adopted electronics and are more efficient relative to the fleet average. It is also worth noting that the number of times the net was hauled during the most recent trip was associated with greater efficiency, although the coefficients are not significant.

Tables 7 and 8 show the comparisons of the means and variances of technical efficiency by adopter category for our preferred functional form. The results from both tables largely support a skill-diluting theory of technical change for both technology types, although this result is clearer for the net hauler. Recall that these technical efficiencies are estimated relative to the frontier of each adopter type. The tests shown in Table 7 clearly demonstrate that average technical efficiency is significantly greater among technology adopters for most specifications. The magnitude of the difference is much greater when the dependent variable is measured as revenue, and is much greater for net hauler adopters. Technical efficiency is 28 percentage points higher for adopters than nonadopters in this category. Average technical efficiency is not significantly greater for electronics adopters when the outcome is measured as total catch, however.

Table 8 tests for equality of variances of technical efficiency between adopters and nonadopters. The first and fifth rows of the table show the standard deviations of technical efficiency for the two groups across different specifications and in every specification the standard deviations are smaller for adopters. We test the significance of these differences with a standard F-ratio test in the second and sixth rows. However, the F-ratio test assumes the data are distributed normally, while our technical efficiency estimates are distributed half-normal by construction. The remaining rows show the Brown-Forsythe robust tests for equality of variances that do not depend on the assumption of normality (Brown and Forsythe 1974). We show the tests using the median as well as the 10% trimmed mean as the measure of central tendency for the tests. In all of the Brown-Forsythe tests across all specifications, the variance of technical efficiency was found to be significantly lower for adopters than nonadop-

TABLE 8
Test for Equality of Variances of Technical Efficiency by Technology Adoption

Dependent Variable: Capital Measure	Revenue			Catch		
	Net Length	Horsepower	Boat Shape	Net Length	Horsepower	Boat Shape
I = Net Hauler						
$\sigma(1):\sigma(0)$	0.05:0.24	0.05:0.24	0.05:0.24	0.05:0.17	0.06:0.16	0.05:0.16
F-ratio	19.3 (0.00)	21.7 (0.00)	19.6 (0.00)	10.4 (0.00)	8.38 (0.00)	13.2 (0.00)
W_{10}	22.3 (0.00)	24.9 (0.00)	20.0 (0.00)	4.18 (0.04)	3.55 (0.06)	4.95 (0.03)
W_{50}	20.7 (0.00)	20.9 (0.00)	17.5 (0.00)	3.55 (0.06)	3.03 (0.08)	4.46 (0.04)
I = Electronics						
$\sigma(1):\sigma(0)$	0.20:0.28	0.21:0.27	0.23:0.28	0.09:0.20	0.11:0.19	0.05:0.20
F-ratio	1.87 (0.08)	1.67 (0.13)	1.52 (0.18)	5.14 (0.00)	3.12 (0.01)	18.7 (0.00)
W_{10}	7.14 (0.01)	5.72 (0.02)	3.21 (0.08)	6.65 (0.01)	4.26 (0.04)	12.1 (0.00)
W_{50}	6.28 (0.01)	5.28 (0.02)	4.11 (0.04)	5.43 (0.02)	3.48 (0.06)	10.0 (0.00)

Note: p-Values in parentheses. W_{10} and W_{50} are the Brown-Forsythe robust tests of variance equality using a 10% trimmed mean and 50% trimmed mean (or median), respectively.

ters at least at the 10% confidence level and in most cases at the 5% level or better.

VI. CONCLUDING REMARKS

We measure relationships between technology use and production outcomes in a common resource extracting industry. Although we do not have the exogenous technology provision necessary for causal estimates, the observed relationships in our cross section of individual vessels in the artisanal Malaysian gill net fishery suggest that new technologies can be skill-diluting. The frontier for net hauler adopters is below the rest of the fleet's frontier and not convincingly above it for electronics users. Adopters operate more efficiently with respect to this interior, "skill-challenged" frontier, with higher mean technical efficiency estimates and lower variance estimates. Technology in this sense may be a way of compensating for a lack of skill.

Yet most fishery participants—adopters and nonadopters alike—remain dissatisfied with fishing as an occupation and continue to fish only because of their inability to find suitable outside options. The anecdotal effect of using a mechanical net hauler, if any, is to reduce reliance on labor, yet adopters still continued to use more labor with less marginal productivity than nonadopters. Furthermore, net haulers are a more expensive technology, requiring specific investment, and are typically adopted by younger boats with longer expected usable lives, which may thus tie these participants to the fishery in the long run. Fishers who claim to have fewer outside options and use fishing as an occupation of last resort tend to be less efficient and have less modern vessel designs, yet continue to reinvest in long-term fishing capital equipment and technology. Cell phones on the other hand may be used in informal networks for fish-finding, rather than finding higher-priced markets. Skill, search, and embodied vessel characteristics seem to drive productivity in this fishery.

There are several implications for policy and development assistance programs. This study highlights the need to take a comprehensive look at technology impacts in artisanal fisheries before promoting technology assistance. Our study raises important questions about the role of technology assistance in any development policy aimed at small-scale users of a common-pool resource. Technology impacts, and by extension, the desirability of technology assistance, may be fishery-specific and depend on relationships between localized skills and technology use. Technical efficiency and technology adoption effects vary by locality even within our sample.

Different technology adoption patterns may impact resource abundance in different ways, a point that has been acknowledged in the literature but not studied in depth and is a subject for future research. Adoption patterns, and by extension technology assistance, can also have differential welfare impacts beyond the impacts on abundance, however. For example, daily and seasonal participation decisions may be more highly correlated when the distribution of productivity is narrower across the fleet. This can affect local labor markets for nonfishing occupations as well as local fish price stability if all fishers decide to fish or not to fish on the same days or in the same months. Even improved short-run outcomes must be weighed against the opportunity cost of foregone alternative policies. Rather than invest in technologies that further tie the less successful fishery participants (i.e., the best candidates for exit) to a declining resource, programs may be better targeted at providing occupational alternatives or other means to exit the fishery.

APPENDIX

Proof of Proposition 1

Recall that $t \in \Re^+$.

Firms pay a price p to invest in technology and a wage w for production inputs. The first order conditions are as follows:

$$f_e(e)g(t;a) = w,$$
$$f(e)g_t(t;a) = p. \qquad [A1]$$

Totally differentiating equations [A1] gives

$$f_{ee} \cdot g \cdot dE + f_e \cdot g_t \cdot dt = -f_e \cdot g_a \cdot da,$$
$$f_e \cdot g_t \cdot dE + f \cdot g_{tt} \cdot dt = -f \cdot g_{ta} \cdot da. \qquad [A2]$$

By Cramer's Rule,

$$\frac{dt}{da} = \frac{-f_{ee}gfg_{ta} + f_{ee}^2 g_t g_a}{f_{ee}gfg_{tt} - f_{eg}^2 g_t^2}. \qquad [A3]$$

To prove point 1 of proposition 1, let $f(e) = e^\gamma$ with $\gamma > 0$ and $g_i(t_i;a_i) = (t_i + a_i)^\alpha$ with $\alpha > 0$, so that technology and ability are gross substitutes. Then production has decreasing returns to scale if $\gamma + \alpha < 1$. When $g_i(t_i;a_i) = (t_i + a_i)^\alpha$, then $f_{ee}gfg_{tt} - f_{eg}^2 g_t^2 > 0$ and $-f_{ee}gfg_{ta} + f_{ee}^2 g_t g_a < 0$, so $dt/da < 0$.

Let t_L denote the level of technology investment by the firm with the lowest managerial ability a_L, and let t_H correspond to $a_H (dt/da) < 0 \Rightarrow t_L > t_H$. The mean of technical efficiency will be larger when technology is present if

$$\frac{1}{2}\left[\left(\frac{a_L + t_L}{a_H + t_H}\right)^\alpha + 1\right] > \frac{1}{2}\left[\left(\frac{a_L}{a_H}\right)^\alpha + 1\right],$$

and the variance will be smaller when technology is present if

$$\frac{1}{12}\left[1 - \left(\frac{a_L + t_L}{a_H + t_H}\right)^\alpha\right]^2 < \frac{1}{12}\left[1 - \left(\frac{a_L}{a_H}\right)^\alpha\right]^2.$$

Both of these inequalities hold if $(a_L + t_L)/(a_H + t_H) > a_L/a_H$, which is true if $t_L > t_H$.

To prove point 2 of proposition 1, let $g_i(t_i;a_i) = a_i(1+t_i)^\alpha$. Then $f_{ee}gfg_{tt} - f_{eg}^2 g_t^2 > 0$ and $-f_{ee}gfg_{ta} + f_{ee}^2 g_t g_a > 0$, so $(dt/da) > 0$, which implies $t_H > t_L$. The mean of technical efficiency will be smaller when technology is present if

$$\frac{1}{2}\left[\frac{a_L(1+t_L)^\alpha}{a_H(1+t_H)^\alpha} + 1\right] < \frac{1}{2}\left(\frac{a_L}{a_H} + 1\right),$$

and the variance will be larger when technology is present if

$$\frac{1}{12}\left[1 - \frac{a_L(1+t_L)^\alpha}{a_H(1+t_H)^\alpha}\right]^2 > \frac{1}{12}\left(1 - \frac{a_L}{a_H}\right)^2,$$

Both of these inequalities hold if $[a_L(1+t_L)^\alpha]/[a_H(1+t_H)^\alpha] < a_L/a_H$, which is true if $t_L < t_H$.

Proof of Proposition 2

Recall $t = 1$ if technology is adopted and $t = 0$ otherwise.

Firms pay a fixed cost F if they adopt the technology. The first-order condition for the firm $f_e(e)g(t;a) = w$ implies a different optimal input demand depending on the presence of the technology, $e^*(w,t,a)$ versus $\hat{e}(w,0,a)$. The firm adopts if

$$f(e^*)g(t;a) - we^* - F > f(\hat{e})g(0;a) - w\hat{e} \Rightarrow$$
$$f(e^*)g(t;a) - f(\hat{e})g(0;a) - w(e^* - \hat{e}) > F. \qquad [A4]$$

We want to show that the marginal net benefit of adoption, the left hand side of [A4], is increasing in managerial ability if the technology is complementary with ability, and decreasing in managerial ability if the technology is a substitute for ability. Differentiating with respect to a and applying the envelope theorem gives

$$f(e^{*})g_{a}(t;a)-f(\hat{e})g_{a}(0;a) \gtrless 0. \qquad [A5]$$

To prove point 1 of proposition 2, again let $f(e)=e^{\gamma}$ and $g_i(t_i;a_i)=(t_i+a_i)^{\alpha}$. Production has decreasing returns to scale if $\gamma+\alpha<1$. When $g_i(t_i;a_i)=(t_i+a_i)^{\alpha}$, then the expression in [A5] is less than zero, and lower-ability managers are more likely to adopt the technology. This is because

$$\frac{f(e^{*})}{f(\hat{e})}<\left(\frac{t+a}{a}\right)^{1-\alpha},$$

$$\left(\frac{t+a}{a}\right)^{\frac{\alpha\gamma}{1-\gamma}}<\left(\frac{t+a}{a}\right)^{1-\alpha},$$

which holds if $\gamma+\alpha<1$. If the manager with the lowest ability adopts and the manager with the highest ability does not, technical efficiency is then distributed

$$TE_i \sim U\left[\left(\frac{a_{\mathrm{L}}+t}{a_{\mathrm{H}}}\right)^{\alpha},1\right].$$

By a similar argument as in the proof of proposition 1.1, the mean of technical efficiency is larger and the variance smaller when technology is present.

To prove point 2 of proposition 2, let $g_i(t_i;a_i)=a_i(1+t_i)^{\alpha}$. Then [A5] is greater than zero and higher-ability managers are more likely to adopt the technology. This is because

$$\frac{f(e^{*})}{f(\hat{e})}>\frac{1}{(1+t)^{\alpha}},$$

which holds if $t>0$. If the manager with the highest ability adopts and the manager with the lowest ability does not, technical efficiency is distributed

$$TE_i \sim U\left[\frac{a_{\mathrm{L}}}{a_{\mathrm{H}}(1+t)^{\alpha}},1\right].$$

By a similar argument as in the proof or proposition 1.2, the mean of technical efficiency is smaller and the variance larger when technology is present.

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