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Can producer groups improve technical efficiency among artisanal shrimpers in Nigeria? A study accounting for observed and unobserved selectivity

Ayobami Adetoyinbo[1,3*] and Verena Otter[2]

*Correspondence: adetoyinbo@gwdg.de; ayobami.adetoyinbo@hu-berlin.de
[3] Present Address: Department of Management of Agricultural Value Chains, Faculty of Life Sciences, Humboldt University Berlin, Invalidenstr. 42, 10115 Berlin, Germany
Full list of author information is available at the end of the article

Abstract

It is widely recognized that participation in producer groups is advantageous for smallholders who must deal with complex production and marketing constraints and dynamic business environments. However, available data on this process are scarce in the fishery sector, while existing evidence is limited by smallholders' potential self-selection into producer groups. This study, therefore, examined the selectivity-corrected role of fisher groups in improving shrimpers' technological and technical efficiency. Using the latest primary data from artisan shrimpers in Nigeria, we applied propensity score matching and Greene's selectivity stochastic production frontier model to control for selection bias from both observable and unobservable factors. Empirical results from our metafrontier approach show that technical efficiency scores for members tend to be overestimated if selectivity is not properly controlled. However, the technical efficiencies and productivities of members were significantly higher regardless of how biases were corrected, implying that participation in fisher groups is positively related to increases in shrimpers' capture and technical efficiency. Further findings suggest that current artisanal fisher groups are "production-oriented" as they ensure that members access vital shrimping inputs at lower costs. With declining returns to scale for members, the study concludes that without public and private support for collective action in the fishery sector, membership in artisanal fisher groups may not lead to significant improvement in shrimpers' productivity. The study discusses several recommendations on how collective action can be further encouraged and developed among artisan fishers.

Keywords: Technical efficiency, Greene's stochastic production frontier, Propensity score matching, Selection bias, Nigerian fisher group, Artisan fishers

Introduction

Over the past decades, smallholders in developing countries have increasingly faced significant transactional challenges in food supply chains caused by constraints in agricultural production and adverse changes in economic, environmental, and sociopolitical structures (AUC/OECD 2019; Ngenoh et al. 2019; Orsi et al. 2017). As a result of smallholders' relatively inefficient production methods, they are often excluded from international high-value food supply chains and limited to less profitable local markets (Barrett et al. 2012). A possible solution to this problem is provided by the growing scientific evidence that collective actions have positive effects on smallholders' economic performance and welfare (Ainembabazi et al. 2017; Chagwiza et al. 2016; Fischer and Qaim 2012; Markelova and Mwangi 2010; Mojo et al. 2017; Ochieng et al. 2018; Verhofstadt and Maertens 2014). Indeed, producer groups and cooperatives are nowadays widely viewed as a valuable institutional arrangement to cope with inefficiencies and exigencies associated with food production and marketing (Martey et al. 2014).

In Africa, fisher groups also bear the responsibility for alleviating supply and marketing challenges (Adetoyinbo and Otter 2020; Mkuna and Baiyegunhi 2019). By acting collectively, fishers can deploy groups' economies of scale, superior information access and effective management of fish resources to enhance their technical ability, productivity, and welfare. However, the relative proportion of artisan fishing households—one of the most socially disadvantaged groups within Africa's agricultural sector—in formal producer groups remains rather low (FAO 2007; WorldFish 2018). This could be an indication of limited economic incentives for group participation as a result of the institutional malfunctioning and inconsistent objectives of the existing fisher group structure (Adetoyinbo and Otter 2020; AUC/OECD 2019). Consequently, the sector remains relatively underdeveloped and non-commercialized and is still barely connected to profitable, high-value markets (Alawode and Oluwatayo 2019; Belhabib et al. 2018; Kobayashi et al. 2015).

The Nigerian shrimp subsector is a primary example of an African fishery sector that remains underdeveloped and has low participation rates by artisanal fisher groups (Adetoyinbo and Otter 2020). Enhanced fishing efficiency obtained via fisher groups could improve artisan fishers' competitiveness and help them to commercialize, target profitable high-value markets, and deal with adverse economic conditions. Despite the government's strong political will to promote agricultural cooperatives and collective action through various policy instruments,[1] no cross-cutting program has been proposed to specifically encourage artisan fishing smallholders to join fisher groups and improve technical efficiency and productivity in the artisanal fishery sector (WorldFish 2018). To this end, appropriate policy measures based on solid scientific evidence about the role and effectiveness of fisher groups should be developed and implemented by governments, agribusiness firms, and extension agents to improve the technical ability and productivity of artisan fishers.

The majority of existing empirical research from which insights on the technical effectiveness of producer groups can be drawn were centered on collective actions in farm-based food sectors like maize, dairy, and coffee (Ainembabazi et al. 2017; Chagwiza et al. 2016; Mojo et al. 2017; Ochieng et al. 2018; Verhofstadt and Maertens 2014). Results from these studies show that the effects of group membership on smallholders' farm and economic performance are mixed, with both positive and negative effects documented

[1] Introduced to propagate farmer groups through the Farm Settlement Scheme, National Accelerated Food Production, Agricultural Development Projects, Agricultural Transformation Agenda in 2011–12 and recently the Agriculture Promotion Policy (FMARD 2016).

(Bernard and Taffesse 2012; Chagwiza et al. 2016; Fischer and Qaim 2012; Hellin et al. 2009). The mixed effects of collective action could be attributed to group heterogeneity of numerous kinds: in goals, organization and governance forms, and property rights distribution. This situation points to the need for a case study and group-specific analyses. However, no studies to date have provided empirical evidence on the selectivity-corrected technical and productivity effects of group membership in African artisanal fisher associations.

The objective of this study is to analyze the selectivity-corrected role of fisher groups in improving the technical efficiency (TE) and productivity of artisan shrimpers in Nigeria. Using recent data obtained from 353 artisan shrimpers (treatment (n = 95) and control (n = 258) groups) in the Nigerian shrimp and prawn[2] subsector, this article contributes to the literature in three ways. First, an unbiased effect of group membership on the TE and technological difference of artisan fishers is estimated using an approach that combines Greene's (2010) stochastic production frontier (SPF) method and propensity score matching (PSM) to correct for bias from selectivity. Concerns over selectivity have been stressed in the general empirical productivity and agricultural economics literature over the last two decades (Greene 2010). Yet, empirical studies (e.g., Abate et al. 2014; Álvarez et al. 2019; Gedara et al. 2012; Hailu et al. 2015; Madau et al. 2017) published on productivity and efficiency effects rarely account for selectivity. Relevant extant studies that did often control for selection bias by employing empirical methods such as propensity score matching, counterfactual endogenous switching regression and inverse Mill's ratio-based frontier models (Abate et al. 2014; Azumah et al. 2019; Ma and Abdulai 2016; Wollni and Brümmer 2012). However, these techniques cannot properly control for selectivity from both observable and unobservable characteristics. This study resolves this limitation by combining Greene's (2010) SPF method and PSM, thus allowing for control of (a) different technological sets for members and nonmembers and (b) sample selection bias from observed and unobserved factors. Consequently, unbiased TE and technical change effects attributable to group membership are estimated.

Furthermore, extant studies have estimated group-specific TE and productivity using several approaches. Abate et al. (2014), for example, analyzed the technical effectiveness of group membership by directly comparing group efficiency scores without controlling for possible group-specific technological differences. However, metafrontier analysis using pooled data is not admissible for different groups since efficiency scores may not cover group-specific frontiers (Huang et al. 2014). Similarly, Abdul-Rahaman and Abdulai (2018) and Ma et al. (2018) conducted a direct comparison of efficiency scores after group-specific frontier estimations, which led to estimations that were made against various production frontiers rather than the pooled metafrontier (Battese et al. 2004; O'Donnell et al. 2008). Instead of performing a metafrontier analysis using only pooled data as done in existing literature, Huang et al.'s (2014) two-step stochastic metafrontier (SMF) regression method was estimated to control for group-specific TE and technological differences. Third, the study estimates a binary probit model to identify factors that influence artisan shrimpers' decisions to join artisanal fisher groups. This study answers

[2] Generally known as shrimp (Kobayashi et al. 2015); therefore, this terminology is used throughout the following text.

a pressing need for identifying membership obstacles. Furthermore, the results have significant policy implications for the institutional improvement of current artisanal fisher groups in Africa.

The remainder of the paper is organized as follows. "Shrimp supply and artisanal fisher groups in Nigeria" section gives details of shrimp supply and artisanal fisher groups in Nigeria. "Conceptual framework and empirical specifications" section presents the study's conceptual framework and empirical specification. The data and models used, as well as the results and discussion, are presented in "Data and model specification" and "Empirical results and discussion" sections, respectively. The last section presents the concluding remarks and policy implications of the study.

Shrimp supply and artisanal fisher groups in Nigeria

In Nigeria, shrimp is the most valuable fish product, with an average annual production of 30,000 metric tons (MT). This production accounted for about 37.20% of total agricultural exports in the third quarter of 2016 and contributed about 3 to 5% of the agriculture share of the gross domestic product (Achoja 2019; NBS 2016; Olaoye and Ojebiyi 2018). Shrimp is mainly found around the Atlantic continental shelf of southern Nigeria, which borders nine coastal states: Ogun, Lagos, Ondo, Edo, Delta, Bayelsa, Rivers, Akwa-Ibom, and Cross River (Olaoye and Ojebiyi 2018). Of these, Ondo has the longest coastline, spanning about 180 km, while Akwa-Ibom and Lagos hold huge wholesaling and retailing markets.

Shrimp is supplied under two production systems, capture and aquaculture. Shrimp aquaculture is largely underdeveloped in the country, accounting for less than 5% of total domestic production (Achoja 2019; Zabbey et al. 2010). Conversely, capture fishery is well established and involves harvesting of products that are naturally occurring in the wild by both industrial trawlers (fishing companies) and smallholder fishers (artisans). While industrial trawlers largely export shrimp products, artisan fishers are important domestically, contributing up to 90% of the total domestic supply (Olaoye and Ojebiyi 2018; Zabbey et al. 2010). Yet, the artisan subsector is dominated by poor fishermen who dwell in the rural coastal areas of the country and use crude tools for their fishing operations.

Not only does the shrimp subsector play a crucial role in the Nigerian economy, it is vital to rural and peri-urban households both as an income source and as a guarantee of food security. With a national average consumption of 13 kg per capita, seafood, including shrimp, supplies about 22% of the national protein intake and is consequently dubbed as "rich food for the poor" (Olaoye and Ojebiyi 2018; WorldFish 2018). However, the increasing human population, the spiraling per capita demand for fish resources, the limited supply of shrimp and the use of traditional methods have contributed to a huge demand–supply gap in the subsector (Achoja 2019; Oluwatayo and Adedeji 2019). To increase domestic production and ensure that the fishery sector moves from conventional low-tech subsistence supply to high-tech commercial production, the Nigerian government has over the years implemented several policies aimed at increasing fishing productivity and efficiency within existing fisher groups (Alawode and Oluwatayo 2019).

Historically, Western-type fisher groups and cooperatives[3] (Menakhem 2001) were introduced to the Nigerian fishery sector by both the government and foreign stakeholders in the 1970s and 1980s during the "Green Revolution," when state-sponsored credit and technical assistance were distributed by cooperatives. Subsequently, the National Fadama[4] Development Project (NFDP) was implemented in the 1990s to promote low-cost technology under a World Bank financing program. The highlight of the program was the implementation of the second and third NFDPs in 2004 and 2008, respectively, under a tripartite financial structure that included the World Bank and federal and state governments. These projects aimed to increase the incomes of farmers and fishers[5] through a community-driven development approach (Alawode and Oluwatayo 2019; Olaoye and Ojebiyi 2018).

The political drive by the national government to support and aggregate fishers into groups for self-sufficient production and marketing began a decade ago. In 2011–2012, the fisheries transformation plan was designed under the Agricultural Transformation Agenda (ATA). ATA was a five-year (2011–2015) program implemented to attain self-sufficiency in fishery production and reduce net imports through aquaculture value chain development. ATA's objective was to create an enabling environment for small-scale fishers to form clusters of fishing communities. These communities were meant to facilitate easy participation in the aquaculture value chain; development of various fish products; producer–market linkup; and the establishment, maintenance, and enforcement of quality standards. Recently, the Agriculture Promotion Policy—a five-year (2016–2020) project—was also established with the intention of refreshing strategies adopted in ATA. However, these policies focused on the development of modern export chains and the popularization of aquaculture, without a concrete national plan for supporting and encouraging collective action among artisan fishers, who rely largely on fish capture and localized value chains (FMARD 2011, 2016; Kobayashi et al. 2015).

In the absence of in-depth insight from existing literature into Nigerian fisher groups, we elicited data on artisanal fisher groups via focus group discussions (FGD) and interviews carried out during a pre-field study. The information reveals that most Nigerian fisher groups today are indigenous organizations with little or no external support. They are sometimes intertwined with, but separate from, groups of extended families (clans), tribes, and religious bodies (Adetoyinbo and Otter 2020; Zabbey et al. 2010). There are

[3] Socio-cultural fisher groups were formed during the pre-colonial and colonial eras by fishers who often migrate from one fishing community to another. These groups were formed based on clans, tribes, and religious bodies, etc., to resolve peculiar challenges such as settlement problems that may arise when migrating into new coastal areas (Hopkins 2020; Menakhem 2001). After the post-colonial era, new sets of contingencies and challenges (e.g., higher demand due to population boom, low productivity, increasing competition, technological advancement, etc.) emerged in the fishery sector, leading to the formation of many artisan fishers into westernized fisher groups (like ARFAN) by the Nigerian regime and foreign agencies (Menakhem 2001). These modern groups are aimed at improving members' overall production and economic performance irrespective of their socio-cultural background and affiliations.

[4] *Fadama* is a Hausa word which means low-lying and flood plain areas characterized by a shallow water table that are located along Nigeria's waterways (Alawode and Oluwatayo 2019).

[5] This was the first time fishers were targeted under the project.

several prominent local fisher groups in different fishing communities, particularly in Lagos. However, most shrimpers belong to the Artisanal Fishers Association of Nigeria (ARFAN), a national association of artisan fishers that has been in existence for over 20 years. This is an indication that ARFAN was formed under previous interventions when international stakeholders were active in the Nigerian fishery sector.

Similar to other local fisher groups, ARFAN seeks to effectively link members to input markets and ensure that fish resources are efficiently produced and exchanged with the processing segment. Thus, existing fisher groups, which are often organized and managed by a minimum of four administrative members—chairperson, vice-chairperson, secretary, and treasurer—are mostly "production-oriented" and inactive in members' marketing activities, like many limited cooperative associations (Grashuis 2018). Additionally, the groups advocate for policy support and interventions for their members by engaging government agencies, private businesses, and other stakeholders through meetings and media. ARFAN collaborates with various stakeholders to tackle issues such as low capture, water pollution from oil company activities, and piracy in the Niger Delta. However, there is no indication that members recently received technological assistance from public and private organizations through fisher groups.

Membership in current fisher groups is open, and shrimpers can join by registering and subsequently paying registration and annual dues that differ by location and group. Information from the FGDs reveals that shrimpers become members of fisher groups for several reasons, including commitment to fishery, learning from experienced shrimpers, obtaining necessary production inputs and credit facilities, and getting external support.

Conceptual framework and empirical specifications

In this section, a multistage framework is presented to evaluate the effect of group membership on TE and the productivity levels of the members. We started with the determinants of artisan fishers' decisions to participate in fisher groups. Next, we generated comparable treatment and control groups and then accounted for potential sample selection bias in the SPF model, thereby controlling for both sources of bias: observed and unobserved characteristics.

Artisan fishers' decisions to participate in producer groups

Membership in producer groups is assessed under the presumption that artisan fishers choose between binary options, that is, to be a member or nonmember. It is presumed that shrimpers are risk-neutral and reflect on their possible net benefits (B_M^*) derived from being a member of a producer group and the expected net benefit (B_N^*) derivable from not being a member. Shrimpers are further assumed to be rational individuals who would make a choice that maximized their benefits (i.e., higher shrimping performance). Thus, the conceptual idea suggests that shrimpers will choose to belong to a producer group if $B_i^* = B_M^* - B_N^* > 0$. However, B_i^* cannot be observed, but can be stated as a function of some noticeable characteristics that influence shrimpers' membership decisions, such as individual and shrimping-associated characteristics. Hence, B_i^* is stated as a function of observable variables that is depicted as:

$$B_i^* = \alpha' \boldsymbol{z}_i + w_i, B_i = 1\left[B_i^* > 0\right], \tag{1}$$

where B_i is a dichotomous variable indicating producer group participation with a value equal to 1 and zero otherwise; α' captures parameters to be estimated; $\boldsymbol{z}_i$ depicts observable shrimping and individual characteristics that influence an artisan fisher's decision to join a producer group; and w_i is the error term of the latent variable framework, normally distributed at zero mean and variance σ^2. The likelihood of joining a producer group is therefore given as:

$$\text{Pro}(B_i = 1) = \text{Pro}\left(B_i^* > 0\right) = \text{Pro}\left(w_i > -\alpha'\boldsymbol{z}_i\right) = 1 - F\left(\alpha'\boldsymbol{z}_i\right), \tag{2}$$

where F is the cumulative distribution function for w_i. Here, it is assumed and expected that shrimpers' participation in a producer group is associated with higher capture and TE, compared to shrimpers who are nonmembers (Abdul-Rahaman and Abdulai 2018; Ma and Abdulai 2016).

Stochastic production frontier model

An SPF model, which was concurrently introduced by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), was employed to determine the relationship between single output (y_i) captured by individual shrimper i using a vector of production inputs (x_i). The approach measures TE by depicting the deviance of individual shrimper's capture from the best-practice production frontier. Thus, the general SPF model is defined as:

$$Y_{ij} = f(X, B_M) + \varepsilon_i, \varepsilon_i = v_{ji} - u_{ji} \tag{3}$$

where Y_{ij} is the quantity captured by the ith shrimper; X depicts a vector of variables on inputs and production characteristics; B_M is a binary factor that depicts group membership effect (MEMBERSHIP); v_{ji} reflects the measurement error, omitted variables, and statistical noise; u_{ji} is presumed to be a one-sided random error that captures technical inefficiency; and the subscript j depicts membership groups, namely B_M for group membership and B_N for nonmembership.

Sample selectivity bias in stochastic production function model

Several past studies have employed different approaches to correct for sample selectivity bias that arises from both observed and unobserved attributes in SPF models (Greene 2010; Kumbhakar et al. 2009; Rahman et al. 2009; Rao et al. 2012; Wollni and Brümmer 2012). Kumbhakar et al. (2009) and Rahman et al. (2009) focused on the observed attributes by assuming that selectivity bias erupts when TE is endogenous with the decision to belong to a producer group. This reflects that the error term w_i in the selection Eq. (4) is correlated with ε_i—the error term in the SPF model. Hence, we controlled for selectivity bias from all relevant time-invariant observable variables by employing PSM to match members (MEM) and control (CONN) producers, in line with Bravo-Ureta et al. (2012), De los Santos-Montero and Bravo-Ureta (2017), and Lawin and Tamini (2019).

PSM involves a two-step matching estimation. For the first step, a suitable control group is constructed with observed attributes that are comparable to those of the members. PSM uses a probit or logit model to predict "propensity scores" that are the probabilities of belonging to the treatment group, based on a set of predefined time-invariant covariates. In the second step, the resulting propensity scores are employed to match comparable producers in the control and treatment groups. The approach requires that the common support, overlap condition, and balancing property are satisfied. Based on the matching balance tests between members and nonmembers, ease of interpretation, and intuitiveness (Bravo-Ureta et al. 2012; De los Santos-Montero and Bravo-Ureta 2017; Lawin and Tamini 2019), the matching algorithm most suited for the study is then selected. Overall, even though not all biases are eliminated, PSM is a customary and reliable method in cases such as this, where panel and experimental data are unavailable (Fischer and Qaim 2012).

Conversely, Bravo-Ureta et al. (2012) and Greene (2010) assumed that selection bias comes from unobservable attributes captured by w_i in the selection model and is associated with the error term v_i in the SPF model. Greene (2010) therefore suggested an approach that extends Heckman's design for the linear regression model to correct for selection bias in SPF models. The approach is based on simulated log-likelihood functions, and it is computationally effective when compared with the likelihood functions suggested by Kumbhakar et al. (2009). Accordingly, we accounted for biases from unobservable characteristics by estimating and comparing conventional and sample selection SPF models.

Conventional SPF models were first estimated using pooled unmatched samples, with the binary variable MEMBERSHIP included as an explanatory variable to account for group membership. Next, two SPF models were estimated using data from unmatched observations, one for MEM and another for CONN. A likelihood ratio (LR) test was done to test the equality of pooled and disaggregated frontier models. If the null hypothesis is rejected and MEMBERSHIP has a direct significant effect on the production frontier, then the existence of technological differences would be affirmed among groups. Thus, two distinct SPF models will be re-estimated but corrected for selection bias, as suggested by Bravo-Ureta et al. (2012) and Greene (2010). The aforementioned steps will be repeated for matched samples, resulting in the estimation of another three standard SPF models (one for the pooled sample and two SPF models for MEM and CONN) and two selectivity-correcting SPF models, one each for MEM and CONN. With this approach, we will control for selectivity bias from both observed and unobserved characteristics (Azumah et al. 2019; De los Santos-Montero and Bravo-Ureta 2017), and the final sample selection and SPF models with their error components will then be stated as:

$$\text{Sample selection}: \quad B_i^* = 1\left[\alpha' \boldsymbol{z}_i + w_i > 0\right], \quad w_i \sim N[0,1] \tag{4}$$

$$\begin{aligned} \text{Stochastic production frontier}: \quad & y_i = \beta' \boldsymbol{x}_i + \varepsilon_i, \varepsilon_i \sim N\left[0, \sigma_\varepsilon^2\right] \\ & \left(y_i, \boldsymbol{x}_i\right) \text{ obtained only when } B_i = 1 \end{aligned} \tag{5}$$

$$\begin{aligned} \text{Error component}: \quad & \varepsilon_i = v_i - u_i \\ & u_i = \sigma_u U_i = \sigma_u |U_i|, \text{ where } U_i \sim N[0,1] \\ & v_i = \sigma_v V_i = \sigma_v |V_i|, \text{ where } V_i \sim N[0,1] \\ & (w_i, u_i) \sim N_2\left[(0,1), \left(1, \rho\sigma_u, \sigma_v^2\right)\right] \end{aligned}$$

where B_i is a binary variable equal to 1 for MEM and 0 for CONN; y captures the output variable; $\boldsymbol{z}$ depicts the control variables in Eq. 4; $\boldsymbol{x}$ consists of all inputs in the SPF model; α' and β' contain the parameters to be predicted; $\varepsilon_i = v_i - u_i$ depicts the error component in the SPF model; and ρ is the parameter for sample selection bias.[6]

TE scores from Eq. (5) need to be interpreted carefully, as they are only relevant for group-level comparison and inappropriate for comparing scores between MEM and CONN (Battese et al. 2004; O'Donnell et al. 2008). Instead, following Huang et al.'s (2014) new two-step SMF regression method, the metafrontier approach was employed to estimate TE and technological differences between the groups. In the first step, the traditional maximum likelihood method was applied to estimate the parameters of SPF regression. In the second step, estimates of group-specific frontiers from the first step were pooled and used as dependent variables in the SMF model with one-sided error terms to derive comparable TE scores and technological gaps. This approach separated random shocks (e.g., unforeseen supply push) from technology gaps and allowed for an effective estimation of meta-technology ratios that envelops group technical inefficiencies. The metafrontier model is specified as:

$$y_{ji}^{*} = f^{j}(x_{ji}, \beta^{*})e^{V_{ji}-U_{ji}} \equiv e^{\mathbf{x}'_{ji}\boldsymbol{\beta}^{j}} \tag{6}$$

$$\mathbf{x}'_{ji}\beta^{*} \geq \mathbf{x}'_{ji}\beta^{j} \tag{7}$$

where y_{ji}^{*} depicts the metafrontier output, β^{*} is a vector of metafrontier parameters fulfilling the constraints in Eq. (4) for all i observations, V_{ji} is the random error representing statistical noise, U_{ji} is the nonnegative random error representing technical inefficiency, and β^{j} is the parameter vector associated with the SPFs of MEM and CONN groups. The estimated metafrontier functions were obtained by the two-step stochastic frontier regressions below:

$$\ln y_{ji}^{*} = \ln f^{j}\left(x_{ji}\beta^{*}\right) + V_{ji} - U_{ji}, \quad i = 1, 2, \ldots, N_j \tag{8}$$

$$\ln\widehat{f^{j}}\left(x_{ji}\beta^{*}\right) = \ln f^{M}\left(x_{i}\beta^{*}\right) + V_{ji}^{M} - U_{ji}^{M} \tag{9}$$

where $f^{M}(\cdot)$ is the metafrontier function and $\ln\widehat{f^{j}}\left(x_{ji}\beta^{*}\right)$ is the group-specific frontier estimates from the first step in (6). Since the estimates $\ln\widehat{f^{j}}\left(x_{ji}\beta^{*}\right)$ are group-specific (MEM and CONN), regression (6) was estimated twice. The estimates from MEM and CONN were then pooled to derive Eq. (9). From Eq. (9), the associated TE and the technological gap ratio (TGR), defined as the ratio of production frontier in the jth group to the metafrontier and metafrontier technical efficiency (MTE), were calculated as below (Huang et al. 2014).

$$\mathrm{TE} = \frac{y_{ji}^{*}}{f^{j}(x_{ji}, \beta^{*})e^{V_{ji}}} = e^{-U_{ji}} \tag{10}$$

[6] Further details of the model are presented in Bravo-Ureta et al. (2012) and Greene (2010).

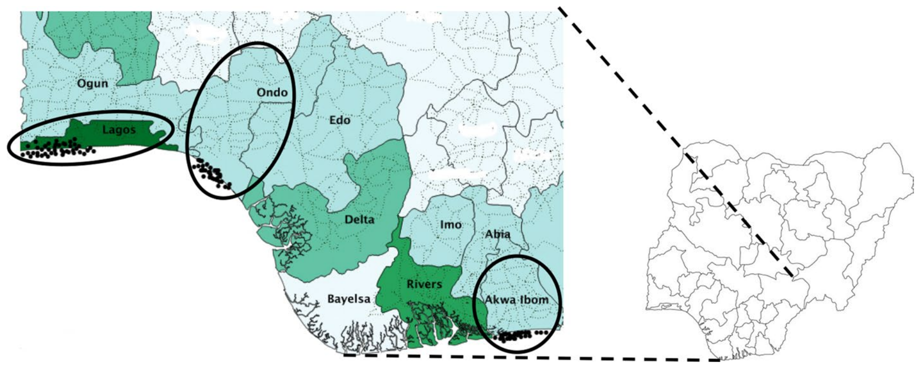

Fig. 1 Map of Nigeria showing shrimping communities and membership distribution

$$\mathrm{TGR} = \frac{\ln f^{j}(x_{ji}\beta^{*})}{\ln f^{M}(x_{i}\beta^{*})} = \mathrm{e}^{-U_{ji}^{M}} = \frac{\mathrm{e}^{\mathbf{x}'_{ji}\beta^{j}}}{\mathrm{e}^{x_{ji}\beta^{*}}} \tag{11}$$

$$\mathrm{MTE} = \frac{y_{ji}^{*}}{f^{M}(x_{ji},\beta^{*})\mathrm{e}^{V_{ji}}} = \mathrm{TGR}_{i}^{j} \times \mathrm{TE}_{i}^{j} \tag{12}$$

Data and model specification

The data used in the study were obtained from a survey conducted from May to August 2018 in 20 shrimping communities located in three states (Lagos, Akwa-Ibom, and Ondo) that represent different socio-cultural regions in Nigeria (see Fig. 1). A multistage sampling technique was employed to first purposively identify states and local shrimping areas and then randomly select 405 producers. The sampling procedure was guided by the information obtained from preliminary FGDs held with artisan shrimpers in 2017 and by extension workers and officials of national research institutes. Both Ondo and Akwa-Ibom have one shrimping area each, Ilaje and Ibeno, respectively, while Lagos has two, Badagry and Eti-osa. All four of these areas were included in this study, based on the prevalence of shrimping activities in the area.

Information was collected using a pretested standardized questionnaire that contained questions on artisan fishers' shrimping and marketing activities and individual-level characteristics. Although information on the full season was obtained, only data on the peak season were used for the analysis. We relied on peak season data because artisans often deploy all of their inputs and optimum business and managerial strategies during this period to maximize their capture. Thus, shrimping activities, capture and efficiency values are often found to be highest during the peak season, relative to the off-season when shrimping and managerial activities are minimal (see Lokina 2009). Additionally, observations from producers who do not use engines were dropped since they would have a different technological set and operate on different production frontiers. The final data set contained 353 observations: 95 group members and 258 nonmembers. This

Table 1 Description and summary statistics of key variables

Variable	Description	Mean
Dependent variables		
TOTALCAP[a]	Shrimp caught in peak season (kg)	48,003.93 (1821.02)
MEMBERSHIP	1 If shrimpers belong to a fisher group, 0 otherwise	0.27
Input variables used in SPF model		
ENGINEOPER	Number of outboard engines operated	1.48 (0.79)
FUELCOST	Cost of fuel used per week during peak season (Naira)	181,384.00 (121,022.90)
USEFULSEINE	Useful life of seine (years)	2.18 (1.41)
LEADERSEMP	Number of skippers employed	0.69 (0.91)
HELPERSEMP	Number of helpers employed	1.03 (1.02)
Production characteristics		
HIGHENGCAP	1 If engine capacity is above 40 HP, 0 otherwise	0.02
FISHVILL	1 If fishing community is within 1 km radius of other fishing community, 0 otherwise	0.39
Independent variables		
AGE	Age of respondent (years)	40.20 (11.01)
EXPERIENCE	Years of shrimping experience	17.39 (10.75)
EDUCYEAR	Years of education	8.50 (4.53)
REPEAT	Number of times classes were repeated	0.10 (0.47)
CUSTOMERS	Number of major customers	1.33 (1.49)
FEMLABSHR	1 If household female laborer engaged in shrimping activities, 0 otherwise	0.22
FEMAS	1 If household female laborer belonged to a shrimping group, 0 otherwise	0.18
AKWA-IBOM[b]	1 For Akwa-Ibom, 0 otherwise	0.33
ONDO[b]	1 For Ondo, 0 otherwise	0.89
MOBILE	1 For mobile phone ownership, 0 otherwise	0.05
EXTENSION	1 If respondent had access to extension, 0 otherwise	0.24
CREDIT	1 If respondent had access to credit, 0 otherwise	0.13
TAROAD	1 If respondent had access to tarmacked road, 0 otherwise	0.26
COOP	1 If respondent participated in local financial cooperative, 0 otherwise	0.11
LEADER	1 If respondent was a skipper, 0 otherwise	0.13
SHOCK	1 If respondent had a shock, 0 otherwise	0.68
Observations		353

[a] The dependent variable is the natural log form of total catch. [b]Reference state is Lagos. Standard errors are presented in parentheses

Source: Authors' calculation based on survey data

sample size was comparable to national and other surveys in Nigeria and Sub-Saharan Africa (Mkuna and Baiyegunhi 2019; Sesabo and Tol 2007).

Table 2 Descriptive statistics of key variables in the matching procedure

Variables	Unmatched			Matched		
	MEM	CONN	Diff	MEM	CONN	Diff
	Mean	Mean		Mean	Mean	
TOTALCAP	56,262.54	44,962.97	11,299.56***	55,891	44,735	11,156**
Inputs						
ENGINEOPER	1.63	1.43	0.20**	1.64	1.42	0.22*
FUELCOST	200,483.40	174,351.80	26,131.60**	203,116	180,000	23,116
USEFULSEINE	2.28	2.14	0.14	2.25	2.08	0.17
LEADERSEMP	0.95	0.60	0.35***	0.93	0.61	0.32**
HELPERSEMP	1.34	0.91	0.43***	1.32	1.01	0.32**
Variables in the matching procedure						
AGE	43.87	38.83	5.04***	43.67	43.26	0.41
EXPERIENCE	21.11	16.03	5.07***	20.84	20.39	0.45
EDUCYEAR	8.67	8.10	0.56	8.66	8.56	0.10
REPEAT	0.04	0.12	− 0.07	0.04	0.02	0.02
FEMLABSHR	1.27	1.35	− 0.08	1.25	1.14	0.11
FEMAS	0.41	0.15	0.26***	0.39	0.43	− 0.04
AKWA-IBOM	0.18	0.19	− 0.01	0.19	0.18	0.01
ONDO	0.11	0.41	0.30***	0.11	0.12	− 0.01
MOBILE	0.94	0.88	0.06*	0.94	0.93	0.01
EXTENSION	0.14	0.02	0.12***	0.13	0.06	0.09
CREDIT	0.33	0.21	0.12**	0.30	0.33	− 0.03
CUSTOMERS	2.38	2.58	0.20	2.40	2.13	0.27
SHOCK	0.64	0.69	− 0.05	0.64	0.67	− 0.03
TAROAD	0.36	0.22	0.14***	0.36	0.31	0.05
LEADER	0.08	0.14	− 0.06	0.09	0.10	− 0.01
COOP[a]	0.24	0.07	0.18***	0.23	0.26	− 0.03
Observations	95	258		92	258	

[a] This is a traditional form of cooperation whereby fishers and non-fishers contribute to informal savings and credit associations for their mutual benefit. It represents a more generic form of cooperative association at the local level and captures the social participation of fishers in other groups

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Source: Authors' calculation based on survey data

The framework required a second data set from a PSM procedure that matched members and nonmembers based on individual and shrimping characteristics in the initial data set. As a result, the kernel matching procedure with a bandwidth of 0.025 was used to generate a total of 92 pairs, representing 92 members out of 95 with 258 nonmembers based on the time-invariant variables in Table 1. While the region of common support ranged between 0.000 and 0.986, three members were discarded due to lack of common support (Fig. 2). Those observations for which a suitable match was achieved were then used as the second data set.

Several other PSM methods such as "1-to-1 nearest neighbor without replacement" and other modifications of kernel matching were also used to determine the matching procedure that fits best.[7] A balance *t*-test was performed before and after matching to

[7] "1-to-1 nearest neighbor" and other distance matching resulted in higher standardized biases.

check the distribution of the variables and assess the null hypotheses of equality between the means of observed characteristics for MEM and CONN (see Table 2). The test indicated that the Epanechnikov kernel matching criterion created significantly lower standardized median bias (7.80) and insignificant covariate differences between the MEM and CONN, which suggests better covariate matching and balancing properties than other PSM methods. Table 1 presents the description of the variables used in the matching procedure and estimation of probit and SPF models.

The descriptive information in Table 1 indicates that respondents caught an average of 48,003.93 kg of shrimp during the 2017/2018 peak season. The majority of the respondents operated an average of 1.48 outboard engines that were attached to planked canoes, implying that the respondents were small-scale artisan fishers (Olaoye and Ojebiyi 2018). The outboard engines consumed large quantities of fuel worth an average of 181,384 Naira (~ 505 USD) per week. Other production factors included a seine with an average useful life of two years, a leader who pilots the canoe and a helper that drags the net.

The average age of the respondents was 40.2 years, which falls within the average age bracket (31–40 years) that is often reported for fishers in Nigeria (Alawode and Oluwatayo 2019). Respondents had on average 17.39 years of experience and thus started shrimping at an early age, like fishers in other African countries (Sesabo and Tol 2007). The average educational level of respondents measured by years of formal schooling was 8.5 years, which is equivalent to primary school education and below the educational levels often reported for fishers and fish farmers in the country (Alawode and Oluwatayo 2019). This difference can be explained by the fact that most of the respondents were artisan shrimpers who dwelled in rural coastal communities, near or on brackish and coastal waterways, where both physical and educational infrastructure are generally rudimentary (Adetoyinbo and Otter 2020; Olaoye and Ojebiyi 2018; Zabbey et al. 2010).

The descriptive differences between MEM and CONN before and after matching are presented in Table 2. On average, they indicate that group members used significantly more production factors such as engines, leaders, and helpers than nonmembers, suggesting that members had larger scales of operation. The average age of group members (43.87 years) was significantly higher than that of nonmembers (38.83 years), indicating that relatively older fishers capitalize more on fisher groups. This also translates into experience, as members had an average of 21 years of experience, which was significantly more than that of nonmembers (16 years). Similarly, women in members' households participated more significantly in shrimp-related groups than women in nonmembers' households, which seems to indicate that members could transact shrimps with their female relations and/or use them as an alternative source of fishing information. Data on physical, institutional, and financial infrastructures suggest that group members also had significantly better access to credit, extension, tarmacked roads, and local social activities than nonmembers.

To analyze the SPF of shrimpers and determine the effect of group membership on their capture and technical efficiency, we applied the parametric approach described previously, which was based on Greene (2010) and Bravo-Ureta et al. (2012). In the first step of the approach, a probit model of group membership, described as the sample selection model (4), was estimated to determine the probability of belonging to a producer group. The model is stated as a function of exogenous shrimping and individual attributes ($\boldsymbol{z}$) that influence group membership. The probit model is expressed as:

$$B_i = \gamma_0 + \sum\nolimits_{j=1}^{16} \alpha' \boldsymbol{z}_i + w_i, \tag{13}$$

where B_i is a binary variable equal to 1 for MEM, and 0 otherwise; γ are unknown parameters to be estimated; w is the error term normally distributed as in (4); and $\boldsymbol{z}$ includes the independent variables presented in Table 1. These control variables have been identified in previous studies as the main factors of group membership among smallholders (Abate 2018; Abdul-Rahaman and Abdulai 2018; Chagwiza et al. 2016; Fischer and Qaim 2012; Mojo et al. 2017; Otter et al. 2014).

Nevertheless, EXTENSION and CREDIT in Eq. (13) are time-invariant, as membership in fisher groups could provide fishers with better access to extension and credit services. For example, motivated and connected fishers are not only more likely to already be recipients of extension and credit services, but also more likely to be members of fisher groups, which can supply them with more information and stimulate them to access extension and credit facilities. Accordingly, the EXTENSION and CREDIT explanatory variables are potentially endogenous in predicting fisher group membership. To account for this endogeneity, we followed Wooldridge's (2014) two-step control function (CF) approach. In the first stage, separate regression estimations for EXTENSION and CREDIT were made using a probit model that included instruments and other variables in Eq. (13). Subsequently, the generalized residuals were predicted for each model. Identification in the CF approach required that the instruments used significantly determined EXTENSION and CREDIT but did not directly influence B_i in Eq. (13). We used shrimpers' perceptions about the usefulness of extension services at the village level and creditworthiness at the individual level, which captured the motivation and disposition toward institutional infrastructure as instruments for EXTENSION and CREDIT, respectively (Ragasa and Mazunda 2018). Intuitively, we expected that these instruments would sufficiently correlate with the endogenous variables since they are crucial for the initiation process of accessing extension and credit facilities but would not directly influence group MEMBERSHIP (see Table 10). Shrimpers in fishing communities where extension services are perceived to be generally useful would likely decide to access them, while shrimpers who thought of themselves as creditworthy would be likely to search out and access credit facilities. By controlling for other covariates such as socioeconomic and geographical factors to capture potential variations among fishers, we expect that these instrumental variables would also not be correlated with the error component in Eq. (13). In the second stage of Wooldridge's (2014) approach, the probit model in Eq. (13) was estimated after the generalized residuals predicted in the first step and the endogenous variables (CREDIT and EXTENSION) were added.

Furthermore, for the second step of the selectivity SPF approach, separate SPF models for MEM and CONN were estimated to account for different technological sets. An LR test, in line with the procedure of Bravo-Ureta et al. (2012), was conducted to compare whether the pooled (unrestricted model) or MEM and CONN models (restricted) were appropriate for both matched and unmatched samples. The LR test is expressed as:

$$\mathrm{LR} = 2(lnL_P - (\ln L_M + \ln L_C)), \tag{14}$$

where lnL_P represents the log-likelihood estimates gained for the pooled samples,lnL_M represents the MEM samples, and lnL_C the CONN samples. After preliminary LR tests indicated that Cobb–Douglas (CD) functional form for MEM and CONN (Table 11 in the Appendix) would be preferable, a CD SPF model was chosen to evaluate shrimpers' TE. The CD model is generally defined as:

$$\ln y_i = \beta_0 + \sum\nolimits_{j=1}^{5} \beta_j \ln(\boldsymbol{x}_{ji}) + \sum\nolimits_{k=1}^{7} \delta_k D_{ki} + (v_i - u_i), \quad \mathrm{if} B = 1 \tag{15}$$

where y_i denotes output of shrimper i during the peak season; $(\boldsymbol{x}_{ij})$ is the quantity of input; β and δ are unknown parameters to be estimated; and v_i *and* u_i are the random and inefficiency components of the error term ε_i and they assume a half-normal distribution. The vector $\boldsymbol{x}$ includes conventional shrimping inputs such as ENGINE,[8] FUELCOST, SKIPPER, HELPER, and SEINE. The number of inputs operated during the peak season was used for the SPF estimation, while seine (net) was measured by its useful life which is indicative of product quality. Previous studies have identified these variables as the classical inputs in the fishery subsectors (Álvarez et al. 2019; Esmaeili 2006; Lokina 2009; Madau et al. 2017; Sesabo and Tol 2007). Dummies D_k were also added to control for shrimping characteristics such as shocks, high engine capacity, clustered fishing communities, and location effects (Ondo and Akwa-Ibom). As in Wollni and Brümmer (2012) and Rao et al. (2012), input variables with zero values were controlled for by creating and including a dummy equal to 1 if input variables were equal to zero. Thus, dummies for SKIPPER and HELPER were created to control for 187 and 124 observations, respectively, that did not use these inputs.

Empirical results and discussion

Estimates of producer group participation decisions

Table 3 shows estimates of factors that determined shrimpers' decisions to join fisher groups for both matched and unmatched samples. Marginal effects were also estimated, to allow easy explanation of the estimates. The chi-square test statistics revealed that the parameter estimates were jointly significant at the 1% level in both of the probit models (LR chi2 (18) = 112.86 and 105.77). The results further show that the residuals of EXTENSION and CREDIT predicted from the first step of the CF approach were not statistically significant, indicating that these explanatory variables did not endogenously predict group membership among fishers.

Focusing on the statistically significant characteristics in Table 3, the marginal effects of EDUCYEAR and EXPERIENCE in the unmatched sample showed that years of education and experience had significantly positive effects on shrimpers' group membership decisions. This finding suggests that shrimpers with higher training and experience are more likely to participate in fisher groups. Additional education can improve shrimpers' literacy and cognitive abilities, helping them to understand the significance and advantages of participating in fisher groups. This phenomenon has been documented among

[8] Canoe was excluded, as it is correlated with the number of engines used, i.e., canoes are operated with engines.

Table 3 Probit model estimates of the determinant of membership in fisher group

MEMBERSHIP	Unmatched sample		Matched sample	
	Probit coefficients	**Marginal effects**	**Probit coefficients**	**Marginal effects**
AGE	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)
EXPERIENCE	0.03** (0.01)	0.01** (0.00)	0.03** (0.01)	0.01** (0.00)
EDUCYEAR	0.04* (0.02)	0.01* (0.01)	0.04* (0.02)	0.01* (0.01)
REPEAT	− 0.34 (0.35)	− 0.08 (0.08)	− 0.34 (0.35)	− 0.08 (0.08)
FEMLABSHR	− 0.13* (0.07)	− 0.03* (0.02)	− 0.13* (0.07)	− 0.03* (0.02)
FEMAS	0.71*** (0.21)	0.17*** (0.05)	0.70*** (0.21)	0.16*** (0.05)
AKWA-IBOM	− 1.07*** (0.37)	− 0.25*** (0.08)	− 1.06*** (0.37)	− 0.25*** (0.09)
ONDO	− 1.01*** (0.23)	− 0.24*** (0.05)	− 1.01*** (0.23)	− 0.24*** (0.05)
MOBILE	0.28 (0.32)	0.07 (0.08)	0.28 (0.32)	0.07 (0.08)
EXTENSION	0.38 (0.47)	0.09 (0.11)	0.37 (0.50)	0.09 (0.12)
CREDIT	0.21 (0.23)	0.05 (0.05)	0.19 (0.23)	0.05 (0.05)
CUSTOMERS	− 0.11** (0.05)	− 0.03** (0.01)	− 0.11** (0.05)	− 0.03** (0.01)
SHOCK	− 0.15 (0.23)	− 0.04 (0.05)	− 0.15 (0.23)	− 0.04 (0.05)
TAROAD	0.73** (0.30)	0.17** (0.07)	0.72** (0.30)	0.17** (0.07)
LEADER	− 0.34 (0.29)	− 0.08 (0.07)	− 0.33 (0.29)	− 0.08 (0.07)
COOP	0.55** (0.26)	0.13** (0.06)	0.54** (0.26)	0.13** (0.06)
EXTENSION residual	0.16 (0.27)		0.17 (0.28)	
CREDIT residual	− 0.04 (0.35)		0.03 (0.36)	
Constant	− 1.50** (0.60)		− 1.49** (0.61)	
Log-likelihood	− 149.15		− 148.72	
LR chi2(18)	112.86		105.77	
Number of obs	353		350	

***$p<0.01$, **$p<0.05$, *$p<0.1$. The parameters in the model were estimated using Eq. (13). Standard errors are presented in parentheses

Source: Authors' calculation based on survey data

small-scale farmers in countries such as Ethiopia and China (Bernard and Taffesse 2012; Chagwiza et al. 2016; Ma et al. 2018; Ngenoh et al. 2019). Similarly, with increasing years of experience, shrimpers could build both human and social capital that allows them to join fisher groups.

The findings on female household members are interesting in that shrimpers with more female household members that are engaged in shrimping activities (FEMLAB-SHR) were 3.0 percentage points less likely to join fisher groups, while those with more female household members that belonged to a shrimping group (FEMAS) were 17 percentage points more likely to do so. These findings can be linked to the role female household members play as lead actor and decision-making authority along the supply base of the chain, in which they are generally engaged in activities beyond production, such as processing, and/or serving as alternative sources of market information (Adetoyinbo and Otter 2020; Orsi et al. 2017). In this regard, shrimpers tend to transact shrimps with and/or rely on female household members for important market information but get discouraged from searching for additional information by participating in fisher groups. Conversely, if these female household members belong to shrimp-related associations or market unions (Menakhem 2001), this will motivate shrimpers to join fisher groups as well. These results are consistent with findings in other fishing communities (Oluwatayo and Adedeji 2019; WorldFish 2018) and among smallholder rice farmers in Ghana, where female-headed household members were more willing to participate in economic groups or platforms (Martey et al. 2014).

TAROAD was found to significantly increase shrimpers' probability of participation in fisher groups by 17 percentage points. This is a logical result since access to tarmacked roads (reflecting close distance to roads) reduces transaction costs associated with organizing and participating in fisher groups. Similar results have been reported by Chagwiza et al. (2016) and Fischer and Qaim (2012), who found negative and nonlinear relationships, respectively, between distance to collection centers (including to roads) and group membership. Further consistent with what Fischer and Qaim (2012) found in Kenya, shrimpers who participated in COOP were found to be 13 percentage points more likely to participate in fisher groups. This is because the social capital and networks of smallholders gained through generic community-based groups such as informal saving cooperatives are crucial for participating in more specialized associations such as artisanal fisher groups.

Conversely, location variables such as AKWA-IBOM and ONDO, which captured state, agro-climatic, and environmental properties, showed negative effects on fisher group membership. In terms of business relationships, CUSTOMERS showed a significant negative effect, indicating that shrimpers with many customers were 3 percentage points less likely to participate in fisher groups. A possible explanation is that shrimpers do not seek extra support and information by joining fisher groups because the existence of many trading partners makes them feel less of power imbalance with the buyers (Abate 2018; Orsi et al. 2017; Otter et al. 2014). Finally, insignificant effects were found from variables such as AGE, LEADER, REPEAT, MOBILE, EXTENSION, CREDIT, and SHOCK, which appear to have played less of a role in shrimpers' membership decisions. These results were fairly consistent for matched samples (see Table 3).

Stochastic production frontier estimates

Table 4 presents the estimated parameters of the conventional and selectivity SPF models for MEM and CONN using the unmatched sample, while Table 5 presents the same parameters calculated by using the matched sample.[9] While pooled and

[9] A prior LR test suggested the presence of inefficiency (Table A.1).

Table 4 Parameter estimates for conventional and selectivity SPF models: Unmatched sample

lnTOTALCAP	**Conventional SPF**			**Sample selection SPF**	
	Pooled	**MEM**	**CONN**	**MEM**	**CONN**
	Coeff	**Coeff**	**Coeff**	**Coeff**	**Coeff**
lnENGINEOPER	0.79*** (0.07)	0.69*** (0.13)	0.84*** (0.09)	0.72*** (0.16)	0.83*** (0.11)
lnFUELCOST	0.10** (0.04)	0.16*** (0.06)	0.08 (0.05)	0.14* (0.08)	0.08 (0.06)
lnLEADERSEMP	0.17** (0.08)	0.06 (0.12)	0.23** (0.11)	0.06 (0.19)	0.23* (0.12)
lnHELPERSEMP	− 0.05 (0.13)	0.24 (0.19)	− 0.20 (0.18)	0.23 (0.29)	− 0.21 (0.20)
lnUSEFULSEINE	0.06** (0.03)	0.09** (0.04)	0.05 (0.03)	0.09 (0.07)	0.05 (0.04)
ONDO	0.09** (0.04)	0.13 (0.10)	0.07 (0.05)	0.05 (0.13)	0.05 (0.06)
AKWA-IBOM	0.09** (0.04)	0.17** (0.08)	0.05 (0.05)	0.12 (0.10)	0.04 (0.06)
SHOCK	0.07** (0.03)	0.06 (0.06)	0.08** (0.04)	0.06 (0.08)	0.09* (0.05)
HIGHENGCAP	− 0.12 (0.10)	− 0.31** (0.15)	− 0.02 (0.13)	− 0.30 (0.23)	− 0.01 (0.19)
FISHVILL	− 0.01 (0.03)	− 0.09* (0.05)	0.01 (0.04)	− 0.11 (0.09)	0.01 (0.05)
Leadercontrol	− 0.04 (0.04)	0.00 (0.07)	− 0.07 (0.06)	− 0.002 (0.09)	− 0.07 (0.06)
Helpercontrol	− 0.03 (0.10)	0.17 (0.16)	− 0.12 (0.13)	0.16 (0.26)	− 0.13 (0.15)
MEMBERSHIP	0.11*** (0.04)				
Constant	9.28 (0.48)	8.44*** (0.68)	9.73*** (0.63)	8.60*** (0.95)	9.66*** (0.72)
λ	1.18*** (0.06)	1.12*** (0.21)	1.28*** (0.07)		
σ^2	0.13*** (0.02)	0.09*** (0.05)	0.14*** (0.02)		
σ_u				0.23* (0.13)	0.28*** (0.07)
σ_v				0.21*** (0.05)	0.25*** (0.04)
$\rho_{(w,v)}$				0.43 (0.47)	− 0.32 (0.34)
Return to scale	1.12	0.93	1.07	0.86	1.06
Number of obs	353	95	258	95	258
Log likelihood	− 51.69	2.96	− 46.22	− 80.40	− 114.32

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The results for pooled, MEM, and CONN models were estimated using Eq. (15). Standard errors are presented in parentheses

Source: Authors' calculation based on survey data

CONN production functions display increasing returns to scale (1.06–1.13), similar to fishers around Lake Victoria in Tanzania (Mkuna and Baiyegunhi 2019), MEM production functions suggest the opposite (decreasing returns to scale) with estimations ranging between 0.84 and 0.93. This result indicates that CONN and MEM are

Table 5 Parameter estimates for conventional and selectivity SPF models: Matched sample

lnTOTALCAP	Conventional SPF			Sample selection SPF	
	Pooled	MEM	CONN	MEM	CONN
	Coeff	Coeff	Coeff	Coeff	Coeff
lnENGINEOPER	0.79*** (0.07)	0.66*** (0.13)	0.84*** (0.09)	0.70*** (0.17)	0.83*** (0.11)
lnFUELCOST	0.10** (0.04)	0.16*** (0.06)	0.08 (0.05)	0.14* (0.08)	0.08 (0.06)
lnLEADERSEMP	0.18** (0.08)	0.08 (0.12)	0.23** (0.11)	0.09 (0.18)	0.23* (0.12)
lnHELPERSEMP	− 0.07 (0.14)	0.22 (0.20)	− 0.20 (0.18)	0.20 (0.30)	− 0.21 (0.20)
lnUSEFULSEINE	0.06** (0.04)	0.09** (0.04)	0.05 (0.03)	0.10 (0.05)	0.05 (0.04)
ONDO	0.09** (0.04)	0.12 (0.10)	0.07 (0.05)	0.05 (0.13)	0.05 (0.06)
AKWA-IBOM	0.08* (0.04)	0.16** (0.08)	0.05 (0.05)	0.11 (0.10)	0.04 (0.06)
SHOCK	0.07** (0.03)	0.07 (0.06)	0.08** (0.04)	0.06 (0.08)	0.09* (0.05)
HIGHENGCAP	− 0.12 (0.10)	− 0.30** (0.14)	− 0.02 (0.13)	− 0.30 (0.22)	− 0.01 (0.19)
FISHVILL	− 0.02 (0.03)	− 0.10* (0.05)	0.01 (0.04)	− 0.12 (0.09)	0.01 (0.05)
Leadercontrol	− 0.04 (0.05)	0.02 (0.07)	− 0.07 (0.06)	− 0.02 (0.09)	− 0.07 (0.06)
Helpercontrol	− 0.04 (0.10)	0.16 (0.16)	− 0.12 (0.13)	0.14 (0.26)	− 0.13 (0.15)
MEMBERSHIP	0.12*** (0.04)				
Constant	9.29*** (0.48)	8.49*** (0.70)	9.73*** (0.63)	8.70*** (0.94)	9.66*** (0.72)
λ	1.19*** (0.06)	1.20*** (0.19)	1.28*** (0.07)		
σ^2	0.13*** (0.02)	0.09*** (0.04)	0.14*** (0.02)		
σ_u				0.24* (0.12)	0.28*** (0.07)
σ_v				0.20*** (0.05)	0.25*** (0.04)
$\rho_{(w,v)}$				0.45 (0.52)	− 0.33 (0.34)
Return to scale	1.13	0.91	1.07	0.84	1.06
Number of obs	350	92	258	92	258
Log likelihood	− 52.17	0.67	− 46.22	− 80.01	− 113.68

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The results for pooled, MEM, and CONN models were estimated using Eq. (15). Standard errors are presented in parentheses

Source: Authors' calculation based on survey data

in the first and second stages of the production function curve, respectively, and that MEM would need to reduce the usage of inputs, especially the number of engines and fuel, to be scale-efficient. The group-specific scale difference can be attributed to two possible causes. First, the neglect of the artisanal fishery sector and fisher groups by policymakers means that the skills, innovativeness, and entrepreneurial abilities of members cannot be further enhanced. Second, increasing production factors such as ENGINEOPER will only lead to input congestion and not double TOTALCAP, because of the limited stock of fish resources in the ocean (Lokina 2009).

As shown in Tables 4 and 5, the null hypothesis of no TE ($\lambda = 0$) was rejected with a probability value of less than 1%. This implies that technical inefficiency contributes significantly to the variation in TOTALCAP for both MEM and CONN. The significance of MEMBERSHIP parameters in the SPF models, as well as the LR tests in Eq. (14), point toward the rejection of the null hypothesis of homogenous technology between MEM and CONN at less than the 5% level (Table 11 in the Appendix). This result confirms that MEM and CONN display different frontiers and provides support for the estimation of distinct group-specific SPF models. Since CD functional form is followed, estimates in the SPF models are interpreted as partial production elasticity that depicts percentage changes in output due to a percentage change of each input.

Focusing on the significant results from the pooled and matched sample of the conventional SPF model in Table 5, the findings reveal that coefficients for four conventional shrimping inputs are positive and significant. Therefore, a 10% increase in any of these inputs would increase TOTALCAP by 7.92% (ENGINEOPER), 1.02% (FUELCOST), 1.80% (LEADERSEMP), and 0.60% (USEFULSEINE). This result is supported by findings from other African fishing subsectors where motorized canoe, fuel, skipper, and seine are the main fishing inputs that significantly contribute to fishery capture (Esmaeili 2006; Lokina 2009; Mkuna and Baiyegunhi 2019; Sesabo and Tol 2007).

For the control variable, the location parameters AKWA-IBOM and ONDO, which account for environmental, shrimping, and other geographical characteristics, are also positive and significant, suggesting that shrimpers in these states are performing better relative to those in Lagos. This is likely because Lagos, Nigeria's main industrial hub, is characterized by many large industrial facilities with operations that adversely affect the stock and rejuvenation of fish resources in the surrounding ocean (Alawode and Oluwatayo 2019). Also, there is higher competition for fish resources among the numerous clusters of fishing populations in Lagos than in other shrimping states. Finally, SHOCK, which accounts for occurrences that disrupt shrimping operations during the peak season (e.g., natural disasters and human activities such as bad water and religious activities) surprisingly has a significantly positive effect on TOTALCAP, especially for CONN. Since the shrimping subsector is unregulated (Adetoyinbo and Otter 2020; Belhabib et al. 2018), this result is meaningful in that such disruptions keep shrimpers away from the waters, thereby allowing for the rejuvenation of fish resources and better catch in subsequent shrimping operations.

Furthermore, the $\rho(w, v)$ parameters in the sample selection SPF models (Tables 4 and 5) are not significant, leading to the conclusion that the result does not show statistical support for the existence of selection bias arising from unobserved factors. This implies that the unobservables in the selectivity model are uncorrelated with the error term in the SPF model and that the TE values estimated in the conventional model may have been biased mainly by observable factors (Greene 2010). Further interpretation of the insignificant $\rho(w, v)$ parameters for members and nonmembers suggests that the two groups would not be significantly different in their average behavior caused by unobserved factors if there was no membership in fisher groups (Abdulai and Huffman 2014).

Technical efficiency and catch levels

The average TGR, TE, and MTE scores for the pooled sample, MEM, and CONN were estimated after conventional and sample selection SPF models were implemented from the SMF models in Eqs. (8 and 9). These scores and the statistical t-test of mean variances between MEM and CONN are summarized in Table 6. The average TGR values ranged between 0.993 and 0.994 for group members and 0.996 for nonmembers, suggesting that nonmembers operate with better technology as their production frontier is higher than that of members. A possible reason for this result could be the difference in industry-specific production characteristics (Huang et al. 2014) because most group members (72%) were located in Lagos, where artisan shrimpers generally employ

Table 6 Technical efficiency estimates across SPF models

SPF model	Pooled Mean	Members Mean	Nonmember Mean	Change (%)	*t*-test of means
Unmatched conventional					
Technical efficiency	0.817 (0.00)	0.848 (0.01)	0.803 (0.01)	5.60	4.83***
Metafrontier technical efficiency (MTE)	0.811 (0.00)	0.843 (0.01)	0.800 (0.01)	5.38	4.67***
Technological gap ratio (TGR)		0.994 (0.00)	0.996 (0.00)		3.24***
Unmatched selection corrected					
Technical efficiency	0.817 (0.00)	0.839 (0.01)	0.808 (0.00)	3.84	3.68***
Metafrontier technical efficiency (MTE)	0.813 (0.00)	0.834 (0.01)	0.805 (0.00)	3.60	3.48***
Technological gap ratio (TGR)		0.994 (0.00)	0.996 (0.00)		3.66***
MTE difference (%)	0.25	− 1.08	0.62		
Matched conventional					
Technical efficiency	0.813 (0.00)	0.842 (0.01)	0.803 (0.01)	4.86	4.05***
Metafrontier technical efficiency (MTE)	0.809 (0.00)	0.836 (0.01)	0.800 (0.01)	4.50	3.84***
Technological gap ratio (TGR)		0.994 (0.00)	0.996 (0.00)		4.05***
Matched selection corrected					
Technical efficiency	0.814 (0.00)	0.831 (0.01)	0.808 (0.00)	2.85	2.66***
Metafrontier technical efficiency (MTE)	0.810 (0.00)	0.826 (0.01)	0.805 (0.00)	2.61	2.39**
Technological gap ratio (TGR)		0.993 (0.00)	0.996 (0.00)		5.00***
MTE difference(%)	0.12	− 1.21	0.62		

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Standard errors are presented in parenthesis

Source: Authors' calculation based on survey data shrimping technology inferior to that used in Ondo and Akwa-Ibom. Also, most members in Lagos tend to be individuals living at subsistence level, with below-average capture (~4 tons less than those in Ondo) and less access to new technologies (Additional file 1: Table S1). These individuals join fisher groups to gain knowledge and information that can improve their productivity and market access.

However, it appears that group members were technically more efficient within their group than the nonmembers, with variations in their MTE values largely dependent on group-specific TE scores. Table 6 shows that the average group-specific TE scores for matched MEM in the conventional and selectivity SPF models are 0.845 and 0.835, respectively, and 0.803–0.808 for CONN in both the conventional and sample selectivity SPF models. In contrast, the average MTE values for matched MEM and CONN in the conventional model are 0.840 and 0.800, respectively. While the MTE score for MEM was reduced to 0.826 in the selectivity SPF model, the score for CONN was increased to 0.805 (Fig. 3). Although the MTE values reported in this study are rather high when compared to what has been found in some African fishery sectors (Sesabo and Tol 2007), similar high TE scores have been reported for small-scale fishers in Tanzania and Nigeria (Lokina 2009; Mkuna and Baiyegunhi 2019; Oluwatayo and Adedeji 2019). The result can be attributed to the use of data based on the peak season, for which comparably higher TE values have been recorded in the literature (Lokina 2009; Udong et al. 2010; Viswanathan et al. 2001).

Overall, the difference in shrimpers' MTE scores shown in Table 6 and Figs. 4, 5 seems to be overestimated if selectivity bias is not properly accounted for. Though MTE scores for members in ARFAN and other local fisher groups remained consistently higher than those of nonmembers in both unmatched conventional and selectivity SPF models, the average MTE values of members decreased by 1.21% after the selectivity SPF model was implemented for the matched sample (Figs. 4, 5). These findings are meaningful, in that accounting for selection bias allowed for more efficient estimation of parameters, though it led to a smaller share of group members operating close to the group-specific production frontiers.[10] It is also plausible that the approach employed here has controlled for those observed and hidden characteristics that members of current fisher groups collectively rely on to drive individual performance. Nevertheless, the technical efficiency scores of members were higher than those of nonmembers regardless of the model (Figs. 4, 5). This finding therefore goes hand in hand with the general purpose of producer groups in developing countries, which is to enhance the technical ability and performance of members (Fischer and Qaim 2012; Ma and Abdulai 2016), but it contradicts what was found in Ethiopia (Mojo et al. 2017) and Nigeria (Adetoyinbo et al. 2022), where some members were seen not to benefit from farm-based cooperatives and their decision-making processes.

Finally, the effect of MEMBERSHIP on TOTALCAP was estimated and compared, assuming that all shrimpers operated efficiently (Table 7). For this purpose, the average predicted frontier was derived from both the conventional and selectivity SPF models. The predicted differentials in TOTALCAP that depict the distance between MEM and

[10] Additionally, the matching procedure could have dropped high-performing members of fisher groups.

Table 7 Predicted frontier output for unmatched and matched samples

SPF models	Pooled	Members	Nonmembers	Technical change (%)	Test of means
Unmatched conventional					
Mean	57,130.00	64,790.39	54,309.31	19.30	2.64***
Unmatched sample selection					
Mean	56,215.70	60,056.17	54,801.57	9.59	1.36*
Matched conventional					
Mean	57,388.27	66,022.27	54,309.31	21.57	2.90***
Matched sample selection					
Mean	56,542.66	61,302.06	54,845.51	11.77	1.64*

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source: Authors' calculation based on survey data

CONN production frontiers (i.e., technological gap) are presented in Table 7, alongside their respective *t*-tests. Without correcting for observed and unobserved differences, members in ARFAN and other local fisher groups caught more shrimp, with an average predicted frontier of 64.79 MT, than nonmembers with about 54.31 MT. While a statistically significant technical change of about 19.30% was observed in the unmatched conventional SPF model, the technical difference decreased to 11.77% after observed and unobserved characteristics were controlled for. Thus, consistent with the MTE scores previously reported in Table 6, the technical differentials were significantly higher for members in both unmatched SPF models though only at 10% significant levels in the matched sample selection model.[11] Similarly to the explanation of returns to scale, it appears that the lack of a national government plan and stakeholder support has led to a lack of progress in ingenuity, technical capabilities and skills among local fisher groups, and has consequently limited fisher groups' potential for supporting and improving their members' productivity (Adetoyinbo and Otter 2020; Markelova and Mwangi 2010).

Table 8 shows the roles artisanal fisher groups play in improving members' performance. While roughly 11% of the respondents reportedly obtained some public assistance, 14% got their inputs, and 21% were trained through ARFAN with the assistance of better-performing and administrative members (Fig. 3), only 2% reportedly sold their products via the group. This confirms that most fisher groups are "production-oriented," like farmer associations in Meso-America and eastern Chad (Hellin et al. 2009; Orsi et al. 2017). Thus, the effect of group membership on shrimpers' productivity originates from the role ARFAN plays in ensuring that individual shrimpers catch and supply shrimps under reduced sectoral contingencies and market challenges.

Using a control function approach as presented in Table 9, we found that MEM takes advantage of membership in artisanal fisher groups to access critical shrimping inputs such as fuel and labor at lower costs. By procuring fuel collectively and facilitating the establishment of fuel retailers close to shrimping sites, members deploy their bargaining

[11] To test the robustness of these findings, we carried out a selectivity test following the Rosenbaum bounds procedure that detects the presence of hidden bias due to unobserved heterogeneity between group members and non-members (Rosenbaum 2002). By adding the highest estimated value of $\rho(w, v)$ in Table 5 to the default gamma cap (1), the selectivity test shows evidence that is robust to negative hidden bias.

Table 8 Roles of artisanal fisher groups

Indicator	% (Yes)
Do you sell shrimp products through fisher groups?	2.13
Do you get inputs through fisher groups?	14.89
Were you trained through fisher groups?	21.28
Did you obtain public assistance since joining the fisher groups?	10.64

Source: Authors' illustration based on survey data

Table 9 Effect of group membership on input costs

	Total variable costs[a]	Fuel cost[b]	Labor cost[b]	Leader cost[b]
	Coeff	Coeff	Coeff	Coeff
MEMBERSHIP	− 14.48** (7.03)	− 332.16** (155.97)	− 6739.38* (3660.02)	− 5196.67** (2594.33)
Control variables	Yes	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	Yes
EXTENSION residual	1.30 (1.46)	7.05 (32.46)	1104.78 (761.68)	1014.66* (539.90)
CREDIT residual	− 0.40 (1.97)	11.11 (43.78)	− 537.43 (1027.29)	− 687.88 (728.17)
Constant	− 5.72* (3.12)	180.49 (69.25)	1495.24 (1625.09)	647.96 (1151.91)
Number of obs	350	350	350	350

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Control variables used in the model were similar to those specified in Eq. (13). Standard errors are presented in parentheses. [a]Coefficients are presented in millions while [b]in thousands and estimations are based on the matched sample. MEMBERSHIP was instrumented using the number of fisher groups at the village level. For full model results, please refer to Tables S2, S3, S4 and S5 in the additional file provided with this study

Source: Authors' calculation based on survey data

power and economies of scale to reduce the purchasing and logistical costs of fuel, which are otherwise high in most shrimping communities. Moreover, fisher groups are responsible for connecting skillful laborers (e.g., leaders) to members at reduced costs—a task achieved by collectively fixing laborers' wages to levels that are economically viable for both the business owners and laborers.

Concluding remarks and policy implications

In this study, a selectivity-correcting model was used to analyze the role of fisher groups in improving artisan fishers' technical efficiency (TE) and productivity in Nigeria. Using recent cross-sectional survey data collected from 353 artisan shrimpers in three major shrimping communities of Nigeria, this study provides empirical evidence on the technical effectiveness of producer groups and drivers of collective actions among smallholders in the fishery sector of developing countries. Binary probit models were estimated to provide insights into factors that influence artisan shrimpers' decisions to join fisher groups. Additionally, an approach that combines PSM and Greene's (2010) SPF was employed to correct for potential sample selectivity from both observed and unobserved characteristics and estimate unbiased metafrontier TE and productivity effects from participation in artisanal fisher groups.

Results from the probit models reveal that shrimpers' socioeconomic characteristics, involvement of female household members, infrastructural facilities, and social participation in other local activities significantly increase the probability of participating in fisher groups. This confirms findings from the existing literature in which poor rural smallholders with limited infrastructure and social engagements were neglected in collective actions (Fischer and Qaim 2012; Verhofstadt and Maertens 2014). The result that shrimpers whose female household members participate in a shrimp-related association have the highest probability of joining a fisher group corroborates the particularly important role and influence that women fishers have on the economic decisions of artisan fishers in Africa compared to producer groups and cooperatives in farm-based subsectors (Menakhem 2001; Oluwatayo and Adedeji 2019; WorldFish 2018).

Analyses of the SPF models provide details about the main shrimping inputs used by artisan fishers. The results show that motorized canoe, fuel, skipper, and seine (net) are the most important production factors that contribute significantly to the quantities of shrimp caught by artisan shrimpers in Nigeria. Furthermore, the TE scores estimated from separate SPF models reveal that the average TE for shrimpers during the peak season was 81.53%, with most shrimpers ranging between 80.30% and 84.80%. This result leads to the conclusion that shrimpers in Nigeria are technically inefficient in deploying their inputs to capture shrimp. Hence, shrimpers have the opportunity to increase their total shrimp catch by 18.47% if they can use available socioeconomic and institutional resources to better deploy their production inputs under current shrimping technology.

Additionally, distinct SMF models were estimated to determine TE and productivity effects attributable to fisher group membership. The SPF estimates show no strong evidence for the presence of selection bias, but suggest that TE and productivity values are overestimated for members in non-selectivity models. The MTE values for members ranged between 82.60% and 84.30% and between 80.00% and 80.50% for nonmembers, depending on how selectivity biases were corrected. Nevertheless, positive TE and productivity effects were documented in conventional and selectivity SMF models, suggesting that participation in fisher groups such as ARFAN leads to improvement in shrimpers' technical efficiency and productivity. Moreover, the "production-oriented" roles of artisanal fisher groups, like the dairy cooperatives in Ethiopia (Chagwiza et al. 2016) and sesame farmers' organizations in eastern Chad (Orsi et al. 2017) indicate that existing fisher groups are pro-poor. Present artisanal fisher groups appear to improve the productivity of their members by engaging in collaborative activities that ensure individual shrimpers have access to key shrimping inputs at lower purchasing and logistical costs and catch shrimps under reduced uncertainties and market challenges. However, since ARFAN members face diminishing returns to scale due to limited innovativeness and entrepreneurial capability, the study concludes that without sufficient support from the public and private institutions, membership in fisher groups may not lead to highly significant improvement in shrimpers' productivity.

Several policy implications emerged from this study. The finding that artisan fishers are technically inefficient amply illustrates the need for increased and concerted fishery policy efforts in Africa that are similar to the 2005 European common fisheries policy. These efforts should encourage development analysts and private agribusiness firms to support the transformation of the artisanal fishery sector (Idda et al. 2009). To further this aim, policymakers should create and implement a concrete national artisanal fishery transformation plan that involves input subsidies and technical support for artisan fishers, just as is done in many farm-based sectors (FMARD 2016).

At the same time, the government should support artisanal fisher groups, since results from the SMF models reveal that they play an important role in improving shrimpers' technical efficiency and productivity. Government policies similar to those established in Ethiopia (Abate et al. 2014) can promote the creation of an enabling legal, economic, and institutional environment for the formation, reorganization and functioning of fisher groups in Nigeria. A policy framework for cooperative development can be implemented within a fishery transformation plan to foster the interconnectedness of existing fisher groups and enhance synergy between public and private stakeholders, thus facilitating collective actions among artisan fishers (Adetoyinbo and Otter 2020).

Furthermore, the "production-oriented" role of current artisanal fisher groups provides policy insights into the equity effects of fisher groups, since they promote even distribution of economic performance and wealth among artisan fishers. Policymakers can improve shrimping operations and the overall technical capability of artisanal fishers by focusing on effective research, as well as development and training that enhance the innovativeness and skillsets of group members (Abdul-Rahaman and Abdulai 2018; Chagwiza et al. 2016; Ma and Abdulai 2016). This is important to drive the productivity effects of fisher groups which are currently hampered by the limited innovativeness and entrepreneurship of members (Adetoyinbo and Otter 2020). Moreover, the functions of artisanal fisher groups need to be broadened beyond the current "production-oriented" activities. Policy measures should be coupled with efficient public–private support and extension services (Adetoyinbo et al. 2022), as seen in Ethiopian agricultural cooperatives (Abate et al. 2014) to incorporate marketing and cooperative functions (e.g., to raise capital, participate along the value chains and determine and/or negotiate prices) within the framework of current artisanal fisher groups (Barrett et al. 2012; FAO 2007; FMARD 2011, 2016; Grashuis 2018; Ragasa and Mazunda 2018; Sambuo et al. 2020). The government can also deploy artisanal fisher groups as a medium to implement far-reaching interventions such as the distribution of subsidized shrimping inputs and technologies aimed at developing the fishery sector, upgrading local fishery supply chains, supporting smallholder access to international high-value food supply chains and driving inclusive agricultural and economic growth (AUC/OECD2019; FMARD 2011; Ngenoh et al. 2019).

Future policy efforts should concentrate on stimulating more artisan shrimpers to join artisanal fisher groups. In this regard, results from the probit models suggest the need for policymakers to focus on strategies that increase the influence of women fishers and reduce the transaction costs of engaging in collective action in rural coastal areas. To achieve this objective, women fishers should be empowered through training, participation in female-oriented integrative cooperative schemes, and asset transfer, while infrastructural facilities such as tarmacked roads should be developed in more shrimping communities to reduce the costs of organizing and engaging in collective action (Adetoyinbo and Otter 2020; Chagwiza et al. 2016; Fischer and Qaim 2012; WorldFish 2018). In particular, as revealed by the probit models, state governments and development stakeholders in Ondo and Akwa-Ibom would need concerted policy measures and strong public–private partnerships to incentivize the formation of and participation in fisher groups.

The study is limited by not covering large samples and variations in shrimpers' socio-demographic characteristics over time. To address this lack, future research could provide more insights into the effect of group membership on productivity by using panel data. Although this study has focused on the productivity effect of fisher groups, future research could also investigate whether group membership in artisanal fisher groups genuinely translates into better welfare for artisan shrimpers in Nigeria and other developing countries.

Appendix

See Figs. 2, 3, 4 and 5, Tables 10 and 11.

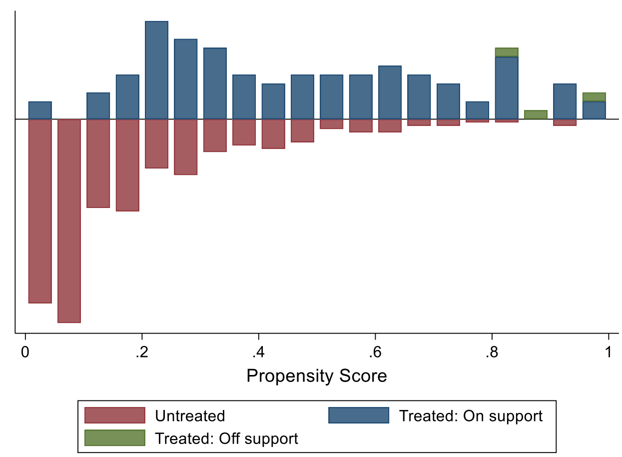

Fig. 2 Common support property for the PSM model. *Source*: Authors' illustration based on survey data

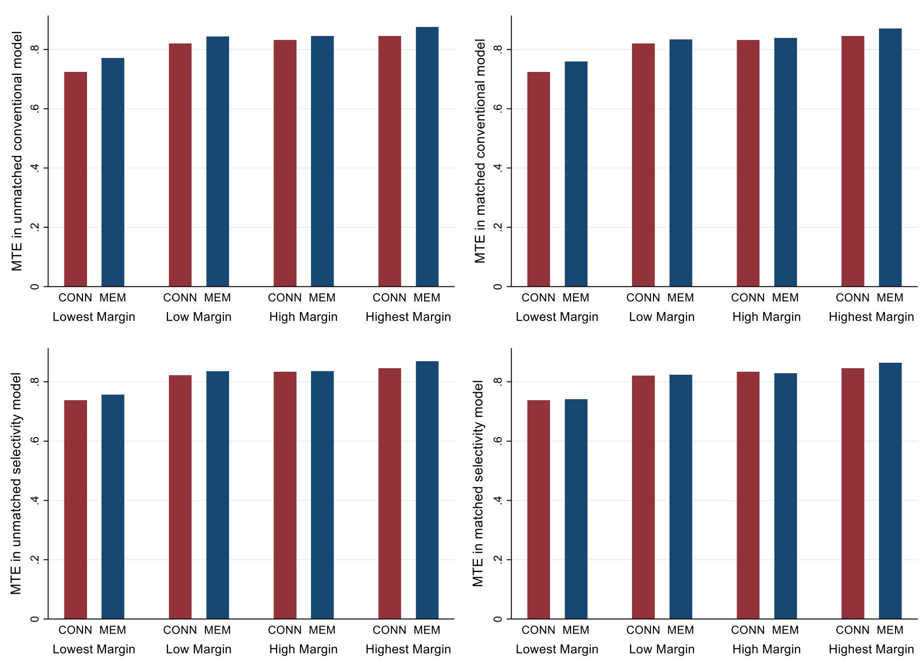

Fig. 3 Metafrontier efficiency scores based on shrimpers' gross margin. *Source*: Authors' illustration based on survey data

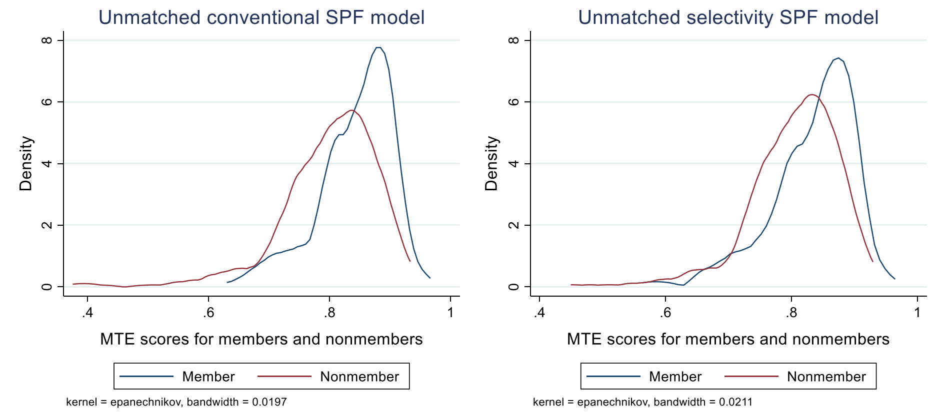

Fig. 4 Metafrontier efficiency scores for members and nonmembers in unmatched SPF models. *Source*: Authors' illustration based on survey data

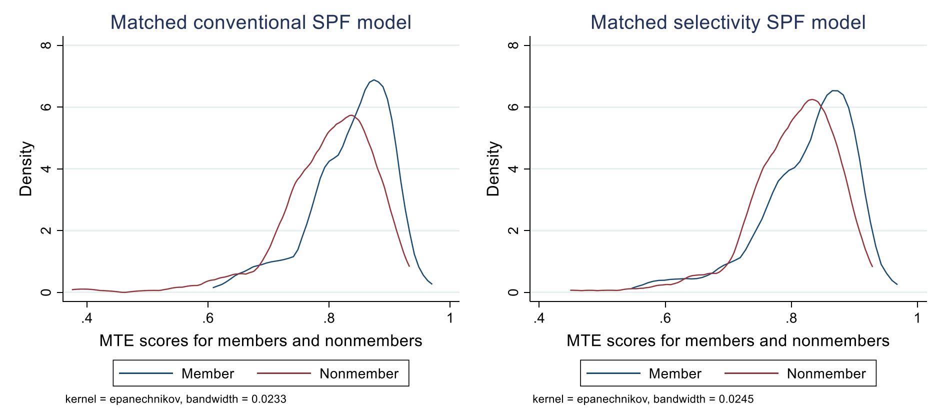

Fig. 5 Metafrontier efficiency scores for members and nonmembers in matched SPF models. *Source*: Authors' illustration based on

Table 10 Probit model addressing potential endogeneity (unmatched samples)

	EXTENSION **Coeff**	**CREDIT** **Coeff**
AGE	− 0.02 (0.19)	− 0.01 (0.01)
EXPEREIENCE	0.04** (0.02)	0.01 (0.01)
EDUCYEAR	0.05 (0.04)	0.05** (0.02)
REPEAT	0.20 (0.24)	0.07 (0.16)
FEMLABSHR	− 0.08 (0.12)	0.10 (0.06)
FEMAS	0.76** (0.32)	0.18 (0.21)
AKWA-IBOM	− 0.64 (0.56)	− 1.55*** (0.37)
ONDO		− 0.19 (0.20)
MOBILE		− 0.60** (0.26)
EXTENSION		− 0.47 (0.40)
CREDIT	− 0.69* (0.40)	
CUSTOMERS	0.01 (0.08)	− 0.07 (0.05)
SHOCK	− 0.12 (0.30)	0.80*** (0.20)
TAROAD	0.28 (0.43)	0.65** (0.30)
LEADER	0.48 (0.38)	− 0.33 (0.27)
COOP	0.63* (0.42)	0.70*** (0.25)
UsefulExtension	4.30** (1.59)	
Creditworthiness		− 0.71*** (0.18)
Constant	− 3.00*** (0.86)	− 0.65 (0.54)
Log-likelihood	− 49.59	154.86
LR chi2(14 and 16)	43.03	77.68
Number of obs	353	353

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. ONDO and MOBILE were dropped in extension model because they perfectly predicted failure to access extension. Standard errors are presented in parentheses

Source: Authors' calculation based on survey data

Table 11 Hypothesis testing for SPF models

Null hypothesis H_0	χ^2 statistics	Degree of freedom	χ^2 critical	Decision
Unmatched conventional				
Cobb–Douglas (CD) is appropriate: $\beta_{ij} = 0$				
Members	10.23	11	19.05	Cannot reject H_0: CD is adequate
Nonmembers	17.54	11	19.05	Cannot reject H_0: CD is adequate
Matched conventional				
Members	11.02	11	19.05	Cannot reject H_0: CD is adequate
Nonmembers	17.54	11	19.05	Cannot reject H_0: CD is adequate
Homogenous technology across channels				
Unmatched conventional	16.86	3	7.05	Reject H_0: No homogenous technology
Matched conventional	13.24	3	7.05	Reject H_0: No homogenous technology
Unmatched conventional	z statistics	*p* value of z		
No technical efficiency effects: $\gamma = 0$				
Members	3.59	0.00		Reject H_0: Frontier not OLS
Nonmembers	7.31	0.00		Reject H_0: Frontier not OLS
Matched conventional				
Members	3.66	0.00		Reject H_0: Frontier not OLS
Nonmembers	7.31	0.00		Reject H_0: Frontier not OLS

Source: Authors' calculation based on survey data

Abbreviations
ARFAN: Artisanal Fishers Association of Nigeria; ATA: Agricultural transformation agenda; CD: Cobb–Douglas; CF: Control function; CONN: Control; FGD: Focus group discussion; LR: Likelihood ratio; MEM: Members; MT: Metric tonnes; MTE: Metafrontier technical efficiency; NFDP: National Fadama Development Project; PSM: Propensity score matching; SMF: Stochastic metafrontier; SPF: Stochastic production frontier; TE: Technical efficiency; TGR: Technological gap ratio.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40100-022-00214-x.

Additional file 1. Table S1. Total shrimp capture by location. **Table S2.** Effect of group membership on total variable cost during the peak season. **Table S3.** Effect of group membership on fuel cost during the peak season. **Table S4.** Effect of group membership on total labor cost during the peak season. **Table S5.** Effect of group membership on leader cost during the peak season. **Table S6.** Probit estimates showing the correlation between perception on extension usefulness and extension access (Full model for unmatched sample). **Table S7.** Probit estimates showing the correlation between perception on extension usefulness and extension access (Reduced model for unmatched sample). **Table S8.** Probit estimates showing the correlation between perception on creditworthiness and credit access (Full model for unmatched sample). **Table S9.** Probit estimates showing the correlation between perception on credit worthiness and credit access (Reduced model for unmatched sample).

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Authors' contributions

AA contributed to conceptualization, methodology, project administration, data acquisition, data curation, formal analysis, interpretation of data, visualization, writing—original draft, review, corrections, and editing, and validation. VO contributed to conceptualization, project administration, validation, writing—original draft, review, corrections, and editing, and supervision. All authors read and approved the final manuscript.

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Availability of data and materials

The supporting data for this article can be provided upon request.

Declarations

Competing interests

The authors do not have any competing interests to declare.

Author details

[1]Department of Agricultural Economics and Rural Development, University of Goettingen, Kreuzbergring 50, 37075 Göttingen, Germany. [2]Business Management & Organisation Group, Wageningen University, Hollandseweg 1, 6706 KN Wageningen, The Netherlands. [3]Present Address: Department of Management of Agricultural Value Chains, Faculty of Life Sciences, Humboldt University Berlin, Invalidenstr. 42, 10115 Berlin, Germany.

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