INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
IFPRI

CGIAR POLICY INNOVATIONS

WORKING PAPER

DECEMBER 2025

Nudging Farmers Toward Disease-Free Shrimp Technology with Financial Incentives

Experimental Evidence from Bangladesh[1]

Muhammad Nahian Bin Khaled[2], Mywish K. Maredia[3], Sudha Narayanan[4], Ben Belton[5], and Razin Iqbal Kabir[6]

[1] The trial is registered with the AEA RCT Registry under RCT ID: AEARCTR-0013688. IRB approval was obtained from the International Food Policy Research Institute (IFPRI) Institutional Review Board (IRB) under IRB no. 00007490 and Michigan State University (STUDY00010661). Local IRB approval was obtained from the Institutional Review Board of the Institute of Health Economics (IHEIRB), University of Dhaka, Bangladesh. This research was supported by the CGIAR Science Program on Policy Innovations. The views expressed in this paper are those of the authors and do not necessarily reflect the views or official positions of IFPRI or CGIAR.

[2] Corresponding author. Department of Agricultural, Food and Resource Economics, Michigan State University. Email: nahian@msu.edu.

[3] Department of Agricultural, Food and Resource Economics, Michigan State University. Email: maredia@msu.edu.

[4] International Food Policy Research Institute. Email: s.narayanan@cgiar.org.

[5] Department of Agricultural, Food and Resource Economics, Michigan State University and International Food Policy Research Institute. Email: ben.belton@cgiar.org.

[6] International Food Policy Research Institute. Email: r.kabir@cgiar.org.

CONTENTS

Abstract **1**

1 Introduction **2**

2 Context **5**

2.1 Study area 5

2.2 Shrimp farming system 7

2.2.1 Pond preparation, stocking and harvesting 7

2.2.2 Type of the PLs 7

2.3 Multi-actor intervention programs in 2023 9

2.4 SPF-PL supply chain and hatchery partnership for randomized intervention 10

3 Study sample and experimental design **10**

4 Data and descriptive statistics **13**

4.1 Data sources and collection 13

4.2 Descriptive statistics 14

5 Conceptual framework **21**

6 Empirical strategy **23**

6.1 Main specification 23

6.2 Understanding the mechanism behind adoption: Heterogeneity analysis 26

7 Results **27**

7.1 Effects of the discount vouchers on adoption behavior 27

7.1.1 Mechanism behind adoption behavior: Heterogeneous treatment effects 31

8 Limitations **45**

9 Discussions and conclusion **46**

References **48**

Appendix **52**

A Sampling strategy for multi-actor intervention program evaluation in 2023 52

B Vouchers and logistics 53

C Power calculation 55

D Attrition and treatment assignment 57

E Motivation behind the intervention 58

F Black-tiger shrimp farming decision and treatment 58

G Black-tiger shrimp farming decision and 2024 flood 59

H Benjamini-Hochberg (BH) False Discovery Rate 59

I Two-Way Fixed Effects Estimates for 2022-2023 60

About the authors 61

Acknowledgments 61

TABLES

Table 1: Pre-intervention summary statistics by treatment groups and balance 15

Table 2: Post-intervention summary statistics in 2024 17

Table 3: Impact of discount vouchers on Mid-grade SPF-PL adoption, expected yield, and expected mortality (full sample and Active farmers): Intention-to-treat (ITT) effects 28

Table 4: Impact of discount vouchers on Premium-grade SPF-PL adoption, expected yield, and mortality: Full sample and Active farmers 29

Table 5: LATE Estimates of Premium-grade SPF-PL Adoption on Expected Yield and Mortality (Active Farmers Only) 30

Table 6: Heterogeneous Impact of Discount Vouchers on Mid-grade SPF-PL Adoption by Prior Participation in the 2023 Multi-Actor Intervention 32

Table 7: Heterogeneous Impact of Discount Vouchers on Premium-grade SPF-PL Adoption by Prior Participation in the 2023 Multi-Actor Intervention 33

Table 8: Heterogeneous Impact of Discount Vouchers on Mid-grade SPF-PL Adoption by Prior Free Receipt of Mid-grade SPF-PL 35

Table 9: Heterogeneous Impact of Discount Vouchers on Premium-grade SPF-PL Adoption by Prior Free Receipt of Mid-grade SPF-PL 36

Table 10: Heterogeneous impact of discount vouchers by cyclone exposure on the adoption of Mid-grade SPF-PL 38

Table 11: Heterogeneous impact of discount vouchers by cyclone exposure on the adoption of Premium-grade SPF-PL 39

Table 12: Heterogeneous impact of discount vouchers by prior shrimp mortality experience on Adoption of Mid-grade SPF-PL 40

Table 13: Heterogeneous impact of discount vouchers by prior shrimp mortality experience on Adoption of Premium-grade SPF-PL 41

Table 14: Heterogeneous impact of discount vouchers by prior nursing facility use on Adoption of Mid-grade SPF-PL 43

Table 15: Heterogeneous impact of discount vouchers by prior nursing facility use on Adoption of Premium-grade SPF-PL 44

FIGURES

Figure 1: Map of Bangladesh showing study districts (highlighted in orange) 6

Figure 2: Shrimp PL alternatives available in the market 8

Figure 3: Household locations by treatment assignment in the study districts 12

Figure 4: Study timeline 12

Figure 5: Adoption rates of Mid-grade and Premium-grade SPF-PL at different price points (full sample) 19

Figure 6: Adoption rates of Mid-grade and Premium-grade SPF-PL at different price points (conditional on active farming in 2024) 19

Figure 7: CDF of Black-tiger shrimp first stocking date after voucher distribution: Normal PL, SPF-PL, or River-PL 20

Figure 8: CDF of SPF-PL purchase date by treatment (conditional on purchasing) 20

ABSTRACT

Price discounts are a common policy tool to promote agricultural technology adoption in low-income settings, yet their effectiveness may be limited when farmers face uncertainty or have access to familiar alternatives. We test this through a randomized controlled trial with shrimp farmers in southwestern coastal Bangladesh, a region highly exposed to climate shocks. The government promotes Specific Pathogen Free (SPF) post-larvae (PL)—certified as disease-free—to reduce high mortality in shrimp farming. Farmers were randomly offered varying discount levels for two SPF-PL types, differing in size uniformity and market price (proxies for quality), with the highest discount reducing their prices to parity with conventional non-SPF PL. We find no significant effect of discounts on adoption of the lower-priced Mid-grade SPF-PL, characterized by less size uniformity. In contrast, discounts significantly increased adoption of the higher-priced, more uniform Premium-grade SPF-PL, raising uptake by 10–19 percentage points among active shrimp farmers. Larger discounts did not yield higher adoption than smaller ones, indicating diminishing returns to discount generosity. Heterogeneity analyses reveal behavioral and contextual mechanisms: prior exposure to Mid-grade SPF-PL reduced its subsequent adoption but increased responsiveness to Premium-grade, consistent with experience effects and reference dependence. Cyclone exposure dampened treatment responses, suggesting capital constraints, while infrastructure preparedness (e.g., nursing facilities) enhanced uptake. These findings underscore that in high-risk agricultural systems, price incentives alone may not drive adoption unless the promoted input is perceived as effective. Successful promotion strategies must integrate quality assurance with attention to farmer experience, behavioral biases, and vulnerability to shocks.

Keywords: Technology adoption, Aquaculture, Randomized controlled trial (RCT), Price Discounts

JEL Codes: O13, Q16, C93, Q12, O33

1 INTRODUCTION

Encouraging the adoption of improved agricultural technologies in low-income settings remains a persistent challenge, despite their potential to boost productivity and mitigate risk (Mobarak et al., 2012; Gignoux et al., 2023; Ahmed et al., 2020). This puzzle has spurred a rich literature investigating why smallholder farmers often fail to take up seemingly beneficial innovations, particularly when market prices, subsidies, or extension programs seek to reduce adoption costs. A policy response has been to offer targeted discounts or input vouchers to stimulate demand. Well-designed, one-time subsidies can catalyze adoption by easing liquidity constraints, promoting learning, or overcoming coordination failures (Cai et al., 2020; Duflo et al., 2011; Jayne et al., 2018). Yet their effectiveness is highly context-dependent: recent evidence shows that post-shock or high-risk environments may blunt their productivity effects (Gignoux et al., 2023). Ultimately, uptake depends not only on price incentives but also on farmers' perceptions of quality, prior experience, and the availability of competing technologies (Cohen and Dupas, 2010; Fischer et al., 2019).

We examine how price incentives and contextual risks shape technology adoption in the context of a high-stakes agricultural system vulnerable to output shocks: shrimp aquaculture in southwestern coastal Bangladesh. This region is highly exposed to climate risks such as sea-level rise, salinity intrusion, and cyclones, making it a critical setting for studying agricultural adaptation (Haque, 2025; World Bank, 2024; Dasgupta et al., 2008). The shift toward brackish-water shrimp aquaculture is widely recognized as an adaptive livelihood strategy in response to these environmental stressors (Ali et al., 2025; Islam et al., 2014).

Aquaculture has become the fastest-growing food production sector worldwide, now supplying over half of the fish consumed by humans (FAO, 2022; Subasinghe et al., 2009). Within this sector, shrimp ranks among the most valuable and widely traded commodities, generating billions in export earnings and supporting rural livelihoods across Asia and Latin America—regions that produced 3.5 of the 5.5 million tonnes of Vannamei and Black Tiger shrimp in 2022 (Aqua Culture Asia Pacific, 2024; Anderson et al., 2017).

Shrimp exports are an important source of foreign exchange for Bangladesh, earning about USD 300 million in FY 2022–23 and ranking as the country's third-largest export earner (The Business Standard, 2023). Disease outbreaks and concerns about sustainability have repeatedly disrupted global supply chains, spurring greater emphasis on pathogen-free broodstock, bio-secure hatcheries, and internationally recognized quality standards (Bush et al., 2013; Little et al., 2016). As the government works to diversify beyond ready-made garments industry, it aims to modernize the shrimp sector and promote the use of Specific Pathogen Free (SPF) post-larvae as a cornerstone of sustainable growth (Islam, 2008). Post-larvae serve as the primary biological input in shrimp farming, functionally analogous to seeds in crop cultivation. SPF-PL is a disease-free alternative to the commonly used hatchery-sourced PL.

However, farmer resistance to adopting SPF-PL continues to undermine policy goals. With post-stocking mortality rates of 45–50% in recent years, reliance on lower-quality PLs not only reduces farmer profits but also threatens the long-term credibility of the shrimp export industry. These losses far exceed those in staple crops, where pests and disease reduce yields by roughly 22 percent in wheat and 30 percent in rice (Savary et al., 2019).

Farmers in this setting face a choice among multiple PL types that vary in price, perceived quality, and disease risk. Two certified SPF-PL variants are currently available in the market: one with lower size uniformity, often regarded as a mid-grade option (hereafter referred to as Mid-grade SPF-PL), and another with greater size uniformity, marketed as a premium product because of perceived higher quality (Premium-grade SPF-PL).[7] Hence, the latter is more expensive than the former. SPF-PL are derived from domesticated broodstock (reproductively mature adult shrimp) imported from Hawaii and raised in certified biosecure hatcheries, providing farmers with a pathogen-free start. On the other hand, hatcheries producing non-SPF normal PL rely on wild-caught broodstock that often carry pathogens, increasing the likelihood of disease outbreaks on farms. Another option, river-sourced PL—harvested from the wild—is perceived by some farmers as more disease-resistant but is less available and typically more expensive. This complex input market landscape complicates the effectiveness of price-based interventions. Although SPF-PL is promoted as a mortality-reducing innovation for Black Tiger Shrimp (Penaeus monodon: locally known as Bagda), its higher price relative to familiar alternatives raises questions about whether discounts alone can shift farmer behavior.

In the growing literature on agricultural technology adoption, little is known about how price incentives perform when improved but costlier technologies become price-competitive with familiar substitutes. This gap is particularly salient in aquaculture and crop farming, where inputs differ in price, availability, and perceived risk. We address this by evaluating a voucher program that equalizes the effective price of an improved input (SPF-PL) with its primary alternative (normal hatchery PL). Unlike prior studies that distributed inputs for free (Gignoux et al., 2023; Maredia et al., 2025), offered partial discounts (Liverpool-Tasie et al., 2025; Carter et al., 2021), or promoted technologies lacking substitutes (Kremer and Miguel, 2007; Cohen and Dupas, 2010), our experiment directly tests whether price parity with the prevailing alternative can shift farmer behavior in input markets.

A second gap concerns how quality perceptions shape responses to price incentives. Farmers are often highly sensitive to both perceived and actual input quality (Cole and Fernando, 2020; Michelson et al., 2021). The two SPF-PL types in our experiment differ in size uniformity and price—attributes farmers interpret as signals of quality—allowing us to test how adoption varies across quality tiers when prices are experimentally aligned.

Finally, beyond the role of price, our study engages with behavioral and informational mechanisms that condition farmers' responsiveness to new technologies (Mobarak et al., 2012; Beaman et al., 2013; Dar et al., 2024; Aggarwal et al., 2024). Prior experience with a technology can anchor beliefs and affect how new information is interpreted, consistent with models of experiential learning and belief updating (Conley and Udry, 2010; Foster and Rosenzweig, 1995). Reference-dependent utility models suggest that farmers who previously received a product for free may anchor their expectations to that baseline, diminishing the perceived value of discounted offers (Köszegi and Rabin, 2006), although such anchoring may attenuate over time (Dupas, 2014). Furthermore, production shocks—such as natural disasters, and disease-induced shrimp mortality—can make farmers capital constrained or heighten risk salience and shift preferences toward disease-free technologies (Kahneman and Tversky, 1979; Cole et al., 2013). Finally, farm's infrastructure-preparedness may signal confidence in the new technology which can shape a farmer's willingness or capacity to adopt new inputs (Dercon and Christiaensen, 2011). By empirically testing these mechanisms, we aim to unpack how price incentives interact with farmer psychology, experience, and local production dynamics.

[7] In the market, the Mid-grade and Premium-grade SPF-PL is known as "Local" and "Project" SPF-PL, respectively. "Local" and "Project" are used as labels by the producer, but do not denote any formal or technical classification. Moreover, our references to "low" and "high" quality are not based on objective measurements of performance (i.e., yield or mortality rate) but reflect perceived differences between the two SPF-PL types, primarily linked to their size and uniformity—traits commonly associated with quality.

To examine whether demand-side subsidies can shift adoption behavior in competitive input markets, we conducted a randomized controlled trial (RCT) with 1,169 shrimp farmers across Khulna, Bagerhat, and Satkhira in southwestern Bangladesh. The sample was drawn from a pre-existing panel of farmers who had participated in a 2023 multiactor intervention (combining public and private actors), as well as a comparison group of non-participants (Narayanan et al., 2025). That program bundled training, good aquaculture practices, and promoted the use of SPF-PL, enabling us to exploit variation in prior exposure to SPF-PL. The 2023 intervention programs promoted mid-grade SPFPL among the farmers.

In the July 2024 stocking season—absent ongoing program support—farmers were randomly assigned to one of five discount voucher arms (two for Mid-grade SPF-PL and three for Premium-grade SPF-PL) or a control group. Mid-grade SPF-PL retailed at BDT 800 per thousand PL, and Premium-grade at BDT 1,200. The highest voucher brought the effective price of SPF-PL to parity with normal hatchery PL. Vouchers were redeemable through Desh Bangla SPF Hatchery Limited, the only SPF supplier in the region. This evaluation was implemented in partnership with the Department of Fisheries (DoF) as an independently randomized follow-on to the broader aquaculture modernization initiative.

This study aims to understand the effectiveness of price-based incentives and the behavioral mechanisms behind technology adoption in aquaculture. Specifically, we address the following research questions:

1. To what extent do discount vouchers of varying amounts influence the uptake of SPF-PL by type among shrimp farmers in a context where lower-cost but riskier alternatives are widely available, even in credit?
2. Do the discount vouchers generate gains in shrimp yield and reduce shrimp mortality?
3. What underlying mechanisms—such as prior experience, risk perception, or prior infrastructure—shape farmers' adoption decisions?

Randomized voucher assignment allows us to estimate the causal impact of price reductions while examining heterogeneous treatment effects by baseline characteristics. The study also offers a unique setting to explore how prior exposure—via earlier training or product experience—interacts with price incentives.

Using an intent-to-treat (ITT) analysis framework, we find no statistically significant average treatment effect of discount vouchers on the adoption of Mid-grade SPF-PL. This null result appears driven by negative or insignificant responses among farmers who had previously received information, training, or free samples of Mid-grade SPF-PL through the earlier multi-actor intervention—suggesting the presence of experience effects or reference dependence. Although we find little evidence of anchoring specifically to the zero price offered in the previous year, farmers receiving the lowest discount (BDT 50) for Mid-grade SPF-PL became 12.6 percentage point less likely to purchase that SPF-PL, compared to those who did not receive Mid-grade SPF-PL for free. This may underscore the importance of designing time-consistent subsidy programs that include a transition strategy away from full subsidies.

In contrast, price discounts significantly increased adoption of the higher-quality Premium-grade SPF-PL. Assignment to treatment groups for Premium-grade SPF-PL raised adoption by 6–10 percentage points overall, and by 10–19 percentage points among active Black Tiger Shrimp farmers. These results suggest that price incentives are more effective when applied to inputs perceived as higher quality, in contrast to the adoption inertia typically observed in low-income settings (Conley and Udry, 2010).

This positive response enables us to explore downstream effects on yield expectations and mortality risk. However, due to the timing of our endline survey, actual harvest outcomes were not available for all farmers; we therefore rely on self-reported expectations. We do not detect statistically significant effects on expected yield or mortality. That said, Local Average Treatment Effect (LATE) estimates offer suggestive evidence that adoption of Premium-grade SPF-PL may improve expected yields. For Premium-grade SPF-PL, we observe more uptake among multi-actor intervention participants, compared to the nonparticipants. These patterns are consistent with experience-based anchoring, where prior exposure may have shaped beliefs about the value of Mid-grade SPF-PL, diminishing the impact of later price incentives, and switching to better alternative in a discounted price scenario.

Our study makes three key contributions. First, to the best of our knowledge, it provides one of the first experimental evaluations of discount vouchers for technology adoption in the aquaculture sector. This contribution is important given aquaculture's growing role in rural economy, nutrition, and international trade, yet the near absence of causal evidence from this sector. By extending the literature on price incentives, input quality comparison, and farmer behavior into this under-researched domain, the study broadens the evidence base for technology adoption in aquatic food systems. Second, by experimentally varying the magnitude of price discounts, we examine how price responsiveness interacts with exposure to natural disasters. By combining variation in both discount levels and flood exposure, we identify how environmental shocks condition the effectiveness of financial incentives—a question with direct implications for both public subsidy design and private sector marketing strategies. Finally, we analyze how discounts interact with farmers' prior exposure to a structured, multi-actor intervention program. This allows us to separate the effects of price incentives from those of experience and belief formation, offering practical lessons for programs that seek to combine subsidies with training or extension. Overall, our findings contribute to broader debates on technology adoption under risk and liquidity constraints, with implications beyond aquaculture for other input-intensive sectors such as hybrid seeds, livestock vaccines, and improved feed technologies.

2 CONTEXT

2.1 Study area

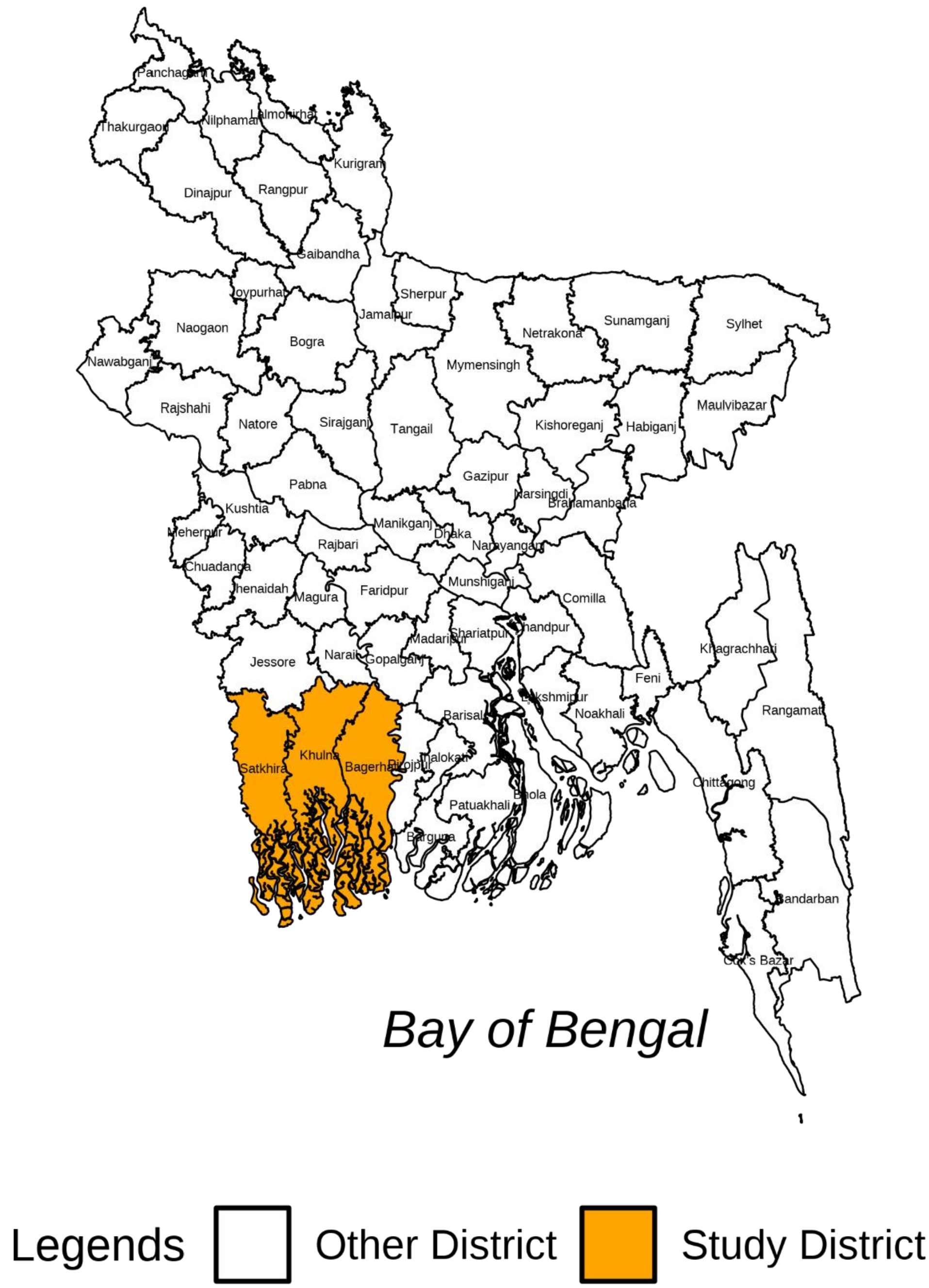
Our study takes place in three districts of the Khulna division in southwestern Bangladesh.

Khulna, Bagerhat, and Satkhira districts—located in the southwestern coastal belt of Bangladesh—offer ideal agro-ecological conditions for shrimp aquaculture, particularly for brackish water species like Black Tiger Shrimp, which is the species of focus of our study. In Figure 1, the three study districts in Bangladesh are highlighted in orange. To their south lies the Bay of Bengal, whose tidal flow supplies the saline water that makes this region uniquely suited for shrimp farming.

These regions benefit from a unique estuarine ecosystem formed by the confluence of major rivers and tidal flows from the Bay of Bengal, which naturally provides saline and semi-saline water critical for shrimp farming. In addition, the flat low-lying terrain allows for easy pond construction and water management. While the freshwater prawn farming started here in 1970s, these districts have emerged as the country's primary hub for shrimp production over the past three decades, supported by a dense network of hatcheries, feed suppliers, and exporters (Belton et al., 2011). Collectively, they contribute a substantial share of Bangladesh's shrimp exports, making them central to the national aquaculture economy.

This setting provides a highly relevant context for studying smallholder participation in modern aquaculture practices, particularly in low-income countries. Shrimp farming in this region has faced longstanding challenges—low productivity, disease outbreaks, and poor access to quality inputs—yet it holds significant export potential and livelihood importance. Studying this context not only allows us to evaluate a policy-relevant intervention with potential scalability, but also contributes to broader debates in development economics on agricultural technology adoption, public-private partnerships, and the role of collective action in improving outcomes for small producers in global value chains.

Figure 1: Map of Bangladesh showing study districts (highlighted in orange)



Source: Authors.

2.2 Shrimp farming system

2.2.1 Pond preparation, stocking and harvesting

In shrimp aquaculture, farmers usually drain ponds and allow them to dry under the sun for about one to two weeks after each harvest. This process helps eliminate harmful pathogens, decompose organic matter, and improve soil oxidation. During pond preparation, farmers apply calcium carbonate to neutralize soil pH, enhance bottom quality, and support beneficial bacteria. They also repair pond dikes and sluice gates, strengthen net fencing to prevent predator entry or shrimp escape, and, for those who practice prerelease nursing, restructure nursery areas. Maintaining a nursery section for post-larvae (PL) improves survival and growth by allowing gradual acclimatization and closer health monitoring before transfer to the grow-out pond. Some farmers use probiotics, potassium permanganate, or similar inputs to maintain water quality, promote beneficial bacteria and control pathogens (Washim et al., 2016). The extent and quality of these practices vary widely across farmers, since effective pond preparation requires capital, technical know-how, and labor. Ponds are typically filled during high tide through shared canals, with mesh screens used to filter incoming water.

Traditional extensive ponds in Bangladesh are shallow, about 2–2.5 feet deep, making them susceptible to temperature fluctuations and water loss that heighten disease risk.

Best practices recommend deepening ponds to 3.5–5 feet to stabilize temperature, improve aeration, and allow higher stocking densities and yield potential (Karim et al., 2011; Belton et al., 2011). Farmers occasionally plant vegetables or fruits on pond embankments to use space efficiently.

Farmers begin their production cycle by releasing post-larvae (PL) into ponds, a process known as stocking. In 2023, about 44.5 percent of farmers had stocked Black Tiger shrimp by February 1, and 97 percent by May, while 88.5 percent reported a second stocking between July and October. These patterns indicate that shrimp production in the region is not strictly seasonal but typically starts early in the year. The timing of stocking decisions depends on the availability of PL, working capital, and pond salinity levels (Belton et al., 2011). Technical guidance is sometimes provided by Department of Fisheries (DoF) extension offices and large buyers. Healthy PL growth is supported through twice-daily feeding. It generally takes three to four months for PL to reach marketable size. Farmers harvest based on commercial grades, which determine price: Super A/A+ (10–15 shrimp/kg), A (16–20), B (21–30), and C (31–40). Larger shrimp fetch higher prices, creating strong incentives to improve survival and growth. Yet production risks remain severe—68 percent of farmers reported shrimp mortality in 2023, with an average loss of nearly 50 percent—highlighting the need for technologies that reduce harvest losses.

2.2.2 Type of the PLs

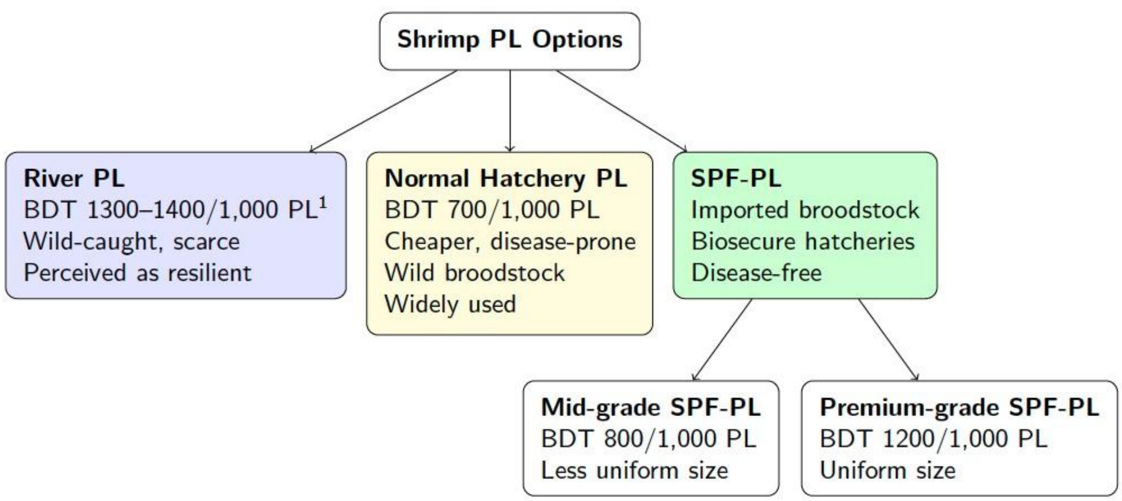
In shrimp farming, post-larvae (PL) serve as the primary biological input, functionally analogous to seeds in crop production. Unlike seeds, PL are living aquatic organisms with limited mobility and heightened sensitivity to environmental conditions, making their handling and survival more delicate and management-intensive. Note that, unlike seeds in crop production, Black-tiger shrimp farmers cannot reuse biologically reproduced PLs from previous cycles, as they are not healthy enough for restocking. As a result, farmers must purchase Black-tiger shrimp PLs from hatcheries, leading to the emergence of a large and growing input market in the study region.

Farmers source PL from three primary channels. The first is river-sourced PL, collected from broodstock in natural river systems and sold by informal traders (locally known as patil wala) in large earthen pots. River-PLs are perceived as more resilient due to their natural origin, though the evidence supporting this belief is mixed (Ahmed and Troell, 2010). Despite these concerns, river-sourced PL are typically sold at the highest price in the market—around BDT 1300–1400 per thousand—likely due to their limited availability and persistent farmer perceptions. Farmers usually purchase river PL with cash, although some traders offer the option to buy on credit. 35% farmers in our sample used river-PL in the baseline year of 2023.

The second is normal hatchery PL, produced in local hatchery facilities without specific pathogen control. They are easily available in the local hatcheries located within the village, making it the most convenient option. Conventional hatcheries rely on wildcaught broodstock, which are often carriers of pathogens such as white spot syndrome virus (WSSV)—yielding PLs that carry infection risk into farms. As with river PL, farmers can often purchase this PL on credit and repay after harvest, making it wellsuited to addressing liquidity constraints. However, access to this credit option may vary across villages. 72% farmers in our sample reported using normal hatchery PL in 2023.

The third is Specific Pathogen Free (SPF) PL, which is bred under biosecure conditions to eliminate common viral pathogens, particularly WSSV. This virus is highly contagious and can lead to serious production losses (Karim et al., 2011). It was first introduced in Bangladesh in 2014 (Washim et al., 2016). However, SPF-PL cannot be produced in traditional hatcheries due to the substantial investment and specialized facilities required (see Section 2.4). They are derived from imported domesticated broodstock (e.g., from Hawaii) raised in biosecure, certified hatcheries that enforce quarantine measures and PCR testing. PLs are dispatched to farmers without known pathogens, providing them a health advantage compared to non-SPF PLs—despite eventual exposure in pond environments.

Figure 2: Shrimp PL alternatives available in the market



Source: Authors.

Two variants of SPF-PL were available in the market during the study period, which we refer to as Mid-grade and Premium-grade SPF-PL. Both were produced by the same hatchery using certified SPF broodstock, but differed in production methods, uniformity in size, and price. Mid-grade SPF-PL were generated by combining nauplii from multiple broodstock and rearing them in high-density tanks for 14–

15 days. This method lowers production costs but results in less uniform size among the PL due to genetic variation and food competition. These PL were sold at a price of BDT 800 per thousand. In contrast, Premium-grade SPF-PL were produced under more controlled conditions. The hatchery used nauplii from a single broodstock per tank and extended the rearing period to around 17 days, reducing within-batch size variation and improving overall quality. These were priced at BDT 1,200 per thousand. Although both variants originate from SPF-certified broodstock and are marketed as SPF-PL, they differ meaningfully in quality, production cost, and market price. In the local markets, they compete not only with each other but also with normal hatchery-produced PL (non-SPF). Farmers follow monoculture with one type of shrimp, or sometimes mix different types of PL.

Based on the assumption that reducing the prevalence of the white spot disease in the pond would likely boost Black-tiger shrimp production, and in turn, the exports, the DoF promoted the use of SPF-PL and encouraged good agricultural practices through the Sustainable Coastal and Marine Fisheries Project (SCMFP) by the DoF, and non-government initiatives. While SCMFP provided only Mid-grade SPF-PL, our field visits revealed the availability of a higher-quality option in the market —Premium-grade—which we included in our study to reflect the broader range of choices available to farmers. Figure 2 summarizes the PL alternatives available in the market.

2.3 Multi-actor intervention programs in 2023

In 2023, three institutional actors in Bangladesh implemented cluster-based intervention programs targeting shrimp farmers in the study region. Throughout this paper, we refer to these collectively as the "multi-actor intervention programs" due to their overlapping objectives and activities aimed at somewhat similar outcomes. These programs are important to contextualize our study, as they shaped farmers' prior exposure to the promoted technology, strengthened the operational linkages between implementing actors and the SPF-PL supply chain, and actively encouraged SPF-PL adoption in the year preceding our randomized intervention. Notably, our study sample is drawn from a broader evaluation of these multi-actor intervention programs (see Section 3). Below, we summarize the key features of the three initiatives:

- **Intervention by the Department of Fisheries (DoF), Government of Bangladesh:** Under the World Bank-funded Sustainable Coastal and Marine Fisheries Project (SCMFP), DoF organized clusters of 20–25 farmers with contiguous ponds and a shared water source. The program required pond deepening, and subsidized or provided free Mid-grade SPF-PL and feed for one year to a subset of farmers. All the farmers in the program received information and technical training on SPF-PL. The aim was to synchronize stocking and harvesting activities across farmers and to facilitate direct sales of harvested shrimp to processors.

- **Intervention by ACI Agrolink Ltd. (ACI):** ACI, a private seafood processor and part of a major Bangladeshi conglomerate, formed similar clusters of 20–25 farmers with adjacent ponds. ACI directly procured shrimp from these farmers for processing. The company offered free SPF-PL (to a subset of farmers), input credit to those purchasing ACI Animal Health feed, bundled insurance packages, and attempted to formalize the arrangement through written buyback contracts.

- **Intervention by Bangladesh Shrimp and Fish Foundation (BSFF):** In collaboration with WorldFish, BSFF organized clusters under the same contiguous pond criterion. Participating farmers committed to shrimp monoculture, received credit through designated banks, and were supplied with free SPF-PL.

The multi-actor intervention programs implemented in the study area aimed to address coordination failures, promote input standardization, and improve market linkages. These programs concluded in 2023. In 2024, with no continuation of these bundled support initiatives, we implemented a separate randomized voucher intervention described in Section 3.

2.4 SPF-PL supply chain and hatchery partnership for randomized intervention

To implement our intervention, we partnered with Desh Bangla SPF Hatchery Limited—the only commercial hatchery producing Specific Pathogen Free (SPF) post-larvae (PL) for Black-tiger shrimp in the study region during 2024. The hatchery is located in Batiaghata, a subdistrict approximately 18 kilometers southwest of Khulna city, accessible via the Khulna–Batiaghata road and situated near the Rupsha River.

As part of its operations, the hatchery sources seawater using a transport vessel, which is then subjected to multi-step purification involving sedimentation, filtration, and disinfection. SPF broodstock, primarily imported from Thailand or India, are maintained in biosecure conditions. These broodstock spawn larvae, which are reared through various developmental stages under stringent biosecurity protocols to ensure the final PLs are free from specific pathogens, thus maintaining their SPF status.

Desh Bangla was an active collaborator in the government-led SCMFP, which promoted both cluster-based farming and the adoption of SPF-PL. Through this initiative, Desh Bangla supplied Mid-grade SPF-PL directly to farmers enrolled in the program. However, Desh Bangla delivers SPF-PL exclusively by truck upon receiving confirmed orders from farmers, either on a cash-on-delivery or prepayment basis, and does not offer sales on credit due to the absence of local operations to manage repayment and follow-up. SPF-PL are delivered in water-filled poly-packs placed inside insulated foam containers, each capable of holding up to 4,000 PLs. Ice cubes are added to the container to prevent temperature rise during transit. Desh Bangla affixes usage instructions and their logo to the container.

3 STUDY SAMPLE AND EXPERIMENTAL DESIGN

Our study builds on a pre-existing sample of 1,222 shrimp farmers from Bagerhat, Khulna, and Satkhira districts in Bangladesh, originally constructed by IFPRI to evaluate the 2023 multi-actor intervention program (see Appendix A, and Narayanan et al. (2025) for details). The sample includes three groups: (i) program participants, (ii) non-participants from the same village, and (iii) non-participants from nearby villages.

To assess how monetary incentives influence the adoption of SPF-PL, we implemented a randomized field experiment among shrimp farmers in our sample. Both types of SPFPL were included in the design: the mid-grade variety, which represented the prevailing market option for many farmers, and the premium-grade variety, which offered a higher quality alternative. Each farmer was randomly assigned to receive one of five discount vouchers or to a control group without a voucher.

Trained field officers visited each household carrying five types of vouchers, a thank-you note, an information card, and an opaque bag containing tokens numbered 1 to 6. After explaining the purpose of the visit, officers read aloud the information card and addressed any questions. The information card explained what SPF-PL is and how it helps reduce white spot disease in Black-tiger shrimp. It also outlined good practices for stocking and releasing SPF-PL, described the two available types (priced at

800 and 1200 taka), and provided details on where and how to purchase them. The field officers then explained the lottery: drawing token #1 corresponded to Voucher 1 (Treatment 1), token #2 to Voucher 2 (Treatment 2), and so on, with token #6 assigning the farmer to the control group (thank-you note only).

Farmers drew one token at random from the opaque bag. Based on the number drawn, they received the corresponding voucher or thank-you note. Vouchers had unique IDs recorded in SurveyCTO against each household ID. The process was simple and well understood. In total, 1,195 farmers were successfully reached and randomized. Appendix Figure B1, and B2 show the materials used in the lottery.

The treatment groups and corresponding voucher values were:

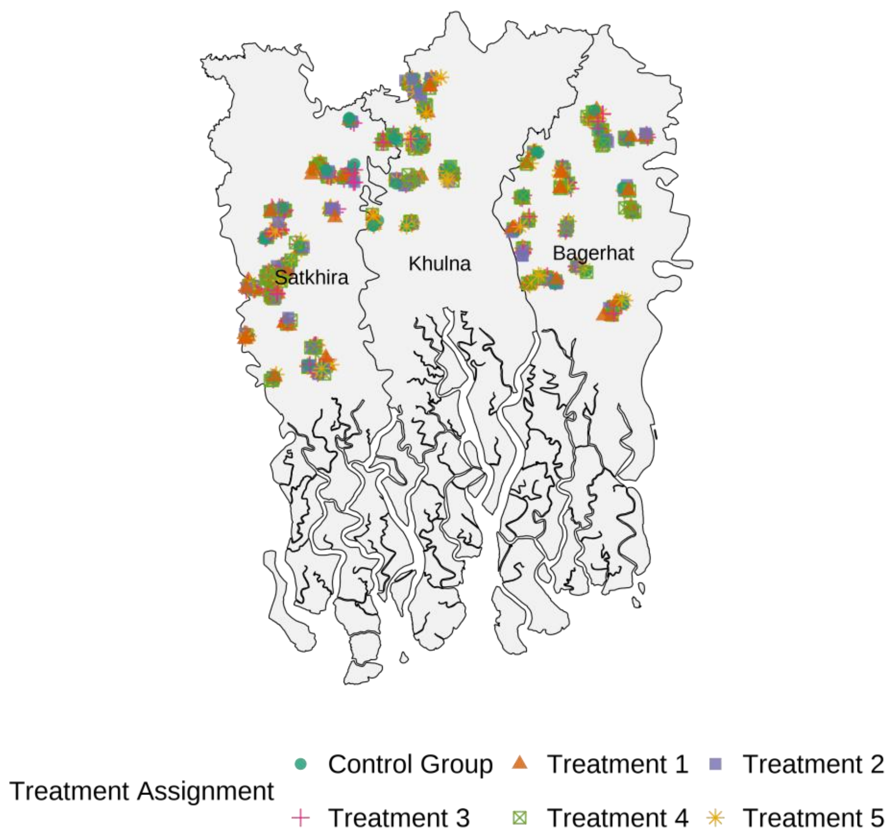
- **Mid-grade SPF-PL** (Market price = BDT 800 per 1,000 PL):
  - **Treatment 1** (n = 208): BDT 100 discount
  - **Treatment 2** (n = 189): BDT 50 discount
- **Premium-grade SPF-PL** (Market price = BDT 1,200 per 1,000 PL):
  - **Treatment 3** (n = 218): BDT 500 discount
  - **Treatment 4** (n = 199): BDT 400 discount
  - **Treatment 5** (n = 191): BDT 200 discount
- **Control group (n = 164):** No voucher; received a thank-you note stating they could purchase SPF-PL from the same supplier at market price.

Appendix C provides a detailed discussion of the power calculations. For Mid-grade SPF-PL, given a control mean of 6.5%, 80% power, and a 5% significance level (twosided test), the minimum detectable effect (MDE) under a conservative scenario is 10 percentage points. In contrast, for Premium-grade SPF-PL, assuming a control mean of 2%, the MDE is 7.2 percentage points, even under conservative assumptions. These calculations suggest that the study is adequately powered to detect policy-relevant increases in adoption. However, it may be underpowered to detect smaller effects, which limits our ability to draw conclusive inferences about more modest impacts.

Figure 3 shows the spatial distribution of the sample farmers by their treatment groups across the three study districts. Because treatment was assigned at the individual level, farmers from different groups are often located near one another.

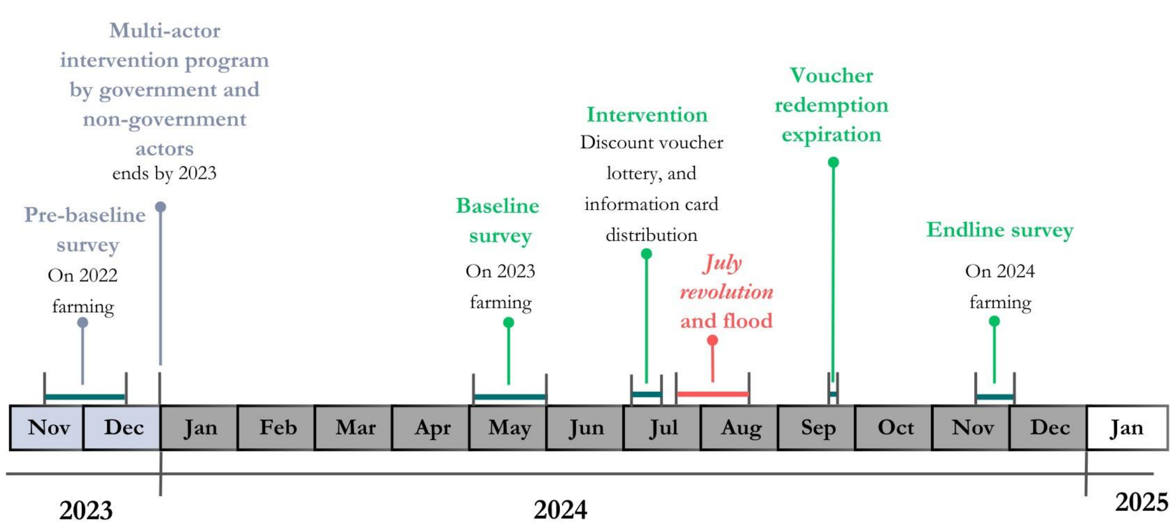
The goal of the vouchers was to make Mid-grade and Premium-grade SPF-PL price-competitive with conventional hatchery PL, which sells for about BDT 700/1,000 PL– approximately BDT 100 less than the market price of Mid-grade and BDT 500 less than that of Premium-grade SPF-PL. The highest discount for each type closed this price gap. The range of discounts enabled us to examine how adoption responds to varying levels of price incentives for two qualities of SPF-PL. To ensure all farmers had equal access to information, we left the information card with them. The card also included a simple form for farmers to record purchase details (price, quantity, and date), which they were asked to report during follow-up verification calls.

Figure 3: Household locations by treatment assignment in the study districts



Source: Authors.

Figure 4: Study timeline



Source: Authors.

Figure 4 shows the study timeline. Between July 8 and July 14, 2024, vouchers offering varying discount levels for two types of SPF-PL were distributed in person using an individual lottery conducted at each farmer's household. Due to operational constraints, we were unable to begin the intervention earlier in the season; as a result, the vouchers were primarily intended to support the second stocking cycle for most farmers.

The supply chain remained unchanged: both treatment and control farmers who wished to purchase SPF-PL were instructed to contact Desh Bangla Hatchery directly. The hatchery handled delivery logistics and did not charge transport fees.

Treatment farmers could redeem vouchers for up to 16,000 SPF-PL units—the recommended quantity for one acre—until September 30, 2024. To prevent misuse, delivery staff verified each farmer's identity by matching voucher names with National ID (NID) cards. In cases where one farmer collected multiple orders for others, they were required to present the corresponding vouchers and NID cards.

Redeemed vouchers were collected by delivery staff, submitted to Desh Bangla, and later shared with the research team for verification and reimbursement. Transactions were cross-checked during follow-up phone surveys. The research team reimbursed Desh Bangla for the value of the discount. In late July, flooding affected parts of the study area. We control for flood exposure in the analysis and explore whether it influenced SPF-PL adoption.

Despite procedures to reduce misreporting, we cannot rule out informal sharing of SPF-PL among farmers, which was beyond our monitoring capacity. However, all reported SPF-PL purchases by control group farmers were made without vouchers, and we found no evidence of treatment contamination. A major political upheaval from July 15 to August 5, 2024, led to regime change and administrative disruptions. While the study villages were unaffected, Desh Bangla's deliveries—routed through Khulna city—were delayed. We control for proximity to Khulna in our models.

Operations resumed in early August. Desh Bangla informed us that voucher redemptions must conclude by September 20, as they planned to suspend operations starting September 25 due to ongoing instability. This prevented some farmers from purchasing SPF-PL as planned. To mitigate this, we informed all farmers on August 15–16 that SPF-PL was again available. If farmers could not purchase due to late stocking schedules, their stated intent to purchase was recorded during the endline survey.

Overall, the supply shock affected all groups similarly and is unlikely to bias treatment effect estimates. Building on the prior multi-actor intervention and the diversity of farmer types in our sample, we now turn to examine how these groups responded differently to price incentives. Specifically, we investigate behavioral mechanisms—such as experience-based learning, informational salience, and reference-dependent preferences from earlier free input provision—that may shape adoption decisions. These channels are described in the conceptual framework that follows.

4 DATA AND DESCRIPTIVE STATISTICS

4.1 Data sources and collection

Our analysis draws on two sources of survey data:

1. **Pre-intervention surveys conducted by IFPRI:** These include two rounds—one in November–December 2023, which collected retrospective data on the 2022 farming season, and a second in

May 2024 (prior to our intervention), which captured information on the 2023 season. We use the May 2024 survey as our baseline. These surveys collected data on adherence to good shrimp farming practices promoted by the prior multi-actor intervention programs, input use and costs, pond characteristics, support received from implementing agencies (DoF, ACI, or BSFF), revenues, and poverty status. Although the earlier round (Nov–Dec 2023) is not central to our main analysis, it provides useful insights into behavioral mechanisms and historical context.

2. **Endline survey conducted for this study:** Implemented between November 21 and December 2, 2024, this phone survey reached 986 out of the 1,195 farmers who received vouchers. To minimize attrition, in-person follow-up surveys were conducted with approximately 19% of non-respondents between December 27, 2024, and January 30, 2025. This resulted in a final sample of 1,169 farmers —an overall response rate of 97.83%. Budget constraints precluded conducting the entire endline survey in person. Appendix Table D1 shows that attrition was unrelated to treatment assignment.

   The endline survey collected detailed information on the type of post-larvae (PL) stocked by pond, farmer perceptions of PL quality, disease incidence and mortality rates, and any shocks experienced during the production cycle.

4.2 Descriptive statistics

Table 1 presents summary statistics for the baseline characteristics of shrimp farmers across treatment arms. The sample comprises 1,169 farmers, evenly distributed across six experimental groups and one control group. The F-test for joint orthogonality in the rightmost column shows whether the treatment assignment is orthogonal (uncorrelated) to baseline covariates. Balance across groups was generally achieved through randomization, as indicated by the high p-values of the F-tests (rightmost column) and the lack of systematic differences across most baseline variables.

The average farmer is approximately 44 years old, with no meaningful differences across arms (p = 0.119). Nearly all farmers are male, with only 0.5% of the sample identifying as female. The sample farmers have an average of 7.3 years of formal schooling. Average pond area is 252 decimals (roughly 2.5 acres), though variation exists across groups, with the control group owning somewhat smaller ponds on average (p = 0.509). The average distance from Khulna city (GPS measured at the zero point: the center of the city) to the farm is about 39 kilometers, with no significant variation across arms.

Baseline exposure to shrimp-related shocks, risk factors and farming practices shows relatively balanced distributions. About 26% reported using Mid-grade SPF-PL in 2023, mainly through the multi-actor intervention program. Less than 1% used Premium-grade SPF-PL. Shrimp mortality was widespread, with 68% of farmers reporting mortality-related losses in 2023.

Roughly half the sample participated in multi-actor intervention programs in 2023, where the interventions aimed to promote better farming practices. In the rest of the sample, about 21% is from the same village where interventions by one of the actors had taken place, and 28.4% is from the neighboring village, with no meaningful differences detected across the treatment groups. The multi-actor intervention programs in 2023 were implemented by three institutional partners: the Department of Fisheries, ACI Agrolink Ltd., and the Bangladesh Shrimp and Fish Foundation. The distribution across intervention actor type appears statistically similar across groups (e.g., Department of Fisheries: 36% overall; p = 0.440).

Table 1: Pre-intervention summary statistics by treatment groups and balance

Variable	Control (1)	Treat 1 (2)	Treat 2 (3)	Treat 3 (4)	Treat 4 (5)	Treat 5 (6)	Total (7)	F-test orthog.
	Treatment Group							
Age (years)	45.561 (1.043)	44.308 (0.849)	44.619 (0.859)	45.807 (0.816)	43.256 (0.875)	43.021 (0.786)	44.424 (0.786)	0.119
1=Female farmer	0.000 (0.000)	0.010 (0.007)	0.000 (0.000)	0.009 (0.006)	0.010 (0.007)	0.000 (0.000)	0.005 (0.002)	0.385
Years of schooling	7.433 (0.324)	7.135 (0.288)	7.376 (0.324)	7.124 (0.317)	7.427 (0.307)	7.518 (0.314)	7.326 (0.127)	0.917
Pond area (decimals)	247.628 (19.160)	267.130 (30.689)	232.332 (16.010)	258.885 (24.609)	224.613 (18.724)	281.812 (24.037)	252.392 (9.505)	0.509
Distance between Khulna city & the farm	37.151 (1.422)	41.178 (1.302)	39.214 (1.318)	40.757 (1.293)	37.402 (1.355)	40.340 (1.377)	39.437 (0.549)	0.151
1=Used Mid-grade SPF-PL in 2023	0.262 (0.034)	0.269 (0.031)	0.270 (0.032)	0.248 (0.029)	0.246 (0.031)	0.230 (0.031)	0.254 (0.013)	0.942
1=Used Premium-grade SPF-PL in 2023	0.012 (0.009)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.010 (0.007)	0.010 (0.007)	0.008 (0.003)	0.923
1=Received free Mid-grade SPF-PL in 2023	0.232 (0.033)	0.207 (0.028)	0.206 (0.030)	0.216 (0.028)	0.201 (0.028)	0.168 (0.027)	0.204 (0.012)	0.771
1=Deepened the pond in 2023	0.189 (0.031)	0.240 (0.030)	0.206 (0.030)	0.193 (0.027)	0.181 (0.027)	0.236 (0.031)	0.208 (0.012)	0.584
1=Had nursing facility in 2023	0.341 (0.037)	0.394 (0.034)	0.402 (0.036)	0.367 (0.033)	0.372 (0.034)	0.356 (0.035)	0.373 (0.014)	0.842
1=Affected by the cyclone Remal in May 2024	0.280 (0.035)	0.312 (0.032)	0.307 (0.034)	0.248 (0.029)	0.322 (0.033)	0.293 (0.033)	0.293 (0.013)	0.606
1=Faced shrimp mortality in 2023	0.652 (0.037)	0.702 (0.032)	0.683 (0.034)	0.679 (0.032)	0.653 (0.034)	0.717 (0.033)	0.682 (0.014)	0.716
Sample type								
1=Multi-actor intervention participant in 2023	0.500 (0.039)	0.500 (0.035)	0.545 (0.036)	0.482 (0.034)	0.503 (0.036)	0.524 (0.036)	0.508 (0.015)	0.858
1=Non-participant (same village)	0.165 (0.029)	0.212 (0.028)	0.233 (0.031)	0.216 (0.028)	0.211 (0.029)	0.204 (0.029)	0.208 (0.012)	0.747
1=Non-participant (neighboring village)	0.335 (0.037)	0.288 (0.031)	0.222 (0.030)	0.303 (0.030)	0.286 (0.032)	0.272 (0.032)	0.284 (0.013)	0.287
2023 intervention: by actor type								
1=Department of Fisheries	0.335 (0.037)	0.365 (0.033)	0.423 (0.036)	0.330 (0.032)	0.347 (0.034)	0.372 (0.035)	0.362 (0.014)	0.440
1=ACI Agrolink	0.073 (0.020)	0.082 (0.019)	0.063 (0.018)	0.078 (0.018)	0.070 (0.018)	0.110 (0.023)	0.080 (0.008)	0.637
1=Bangladesh Shrimp & Fish Foundation	0.091 (0.023)	0.053 (0.016)	0.058 (0.017)	0.073 (0.018)	0.085 (0.020)	0.042 (0.015)	0.067 (0.007)	0.344
1=Does not belong to a cluster	0.500 (0.039)	0.500 (0.035)	0.455 (0.036)	0.518 (0.034)	0.497 (0.036)	0.476 (0.036)	0.492 (0.015)	0.858

Variable	Treatment Group							F-test orthog.
	Control (1)	Treat 1 (2)	Treat 2 (3)	Treat 3 (4)	Treat 4 (5)	Treat 5 (6)	Total (7)	
Pre-intervention beliefs:								
1="SPF-PL is not available in the area"	0.354 (0.037)	0.490 (0.035)	0.450 (0.036)	0.463 (0.034)	0.427 (0.035)	0.508 (0.036)	0.452 (0.015)	0.058*
1="SPF-PL is better than normal PL in production, growth and disease resistance"	0.585 (0.039)	0.630 (0.034)	0.661 (0.035)	0.619 (0.033)	0.643 (0.034)	0.696 (0.033)	0.640 (0.014)	0.344
1="Never heard of SPF-PL"	0.159 (0.029)	0.154 (0.025)	0.138 (0.025)	0.183 (0.026)	0.151 (0.025)	0.115 (0.023)	0.151 (0.010)	0.541
1="SPF-PL is too expensive"	0.207 (0.032)	0.231 (0.029)	0.217 (0.030)	0.170 (0.025)	0.191 (0.028)	0.241 (0.031)	0.209 (0.012)	0.512
1="SPF-PL not effective in disease prevention"	0.024 (0.012)	0.010 (0.007)	0.016 (0.009)	0.023 (0.010)	0.020 (0.010)	0.016 (0.009)	0.018 (0.004)	0.894
1=Would stock Bagda PL in Jul-Dec 2024 (after the intervention)	0.835 (0.029)	0.870 (0.023)	0.873 (0.024)	0.908 (0.020)	0.889 (0.022)	0.916 (0.020)	0.884 (0.009)	0.179
N	**164**	**208**	**189**	**218**	**199**	**191**	**1,169**	
% of sample	**14.029**	**17.793**	**16.168**	**18.648**	**17.023**	**16.339**	**100.000**	

Source: Authors' calculations.

Note: The values for F-tests are p-values. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Treat 1 and 2 received 100 and 50 BDT off on the 800 BDT type, respectively; Treat 3 to 5 received 500, 400, 200 BDT off on the 1200 BDT type, respectively. The control group only received an information card.

The main reasons cited for not adopting SPF-PL were limited availability (45%), lack of awareness (15% of farmers had never heard of it), and high cost (reported by 21% of farmers). A simple regression of 2023 SPF-PL use on a binary indicator for perceiving the technology as "too expensive" in 2023 shows that such perception is associated with a 30 percentage point lower likelihood of adoption, holding other factors constant (see Appendix Table E1). These beliefs are fairly balanced across groups, with the exception of perceived availability ($p = 0.058$), where some treatment groups report slightly higher concern. Through our experiment, we sought to address the availability and awareness barriers uniformly across all study participants, and varied the perceived cost barrier by randomly assigning discount vouchers. Finally, roughly 88% of farmers reported intent to stock Black-tiger PL in the July–December 2024 cycle (after the intervention period), with no significant differences across arms.

Conventional balance tests are often criticized for over-rejecting the null of random assignment, particularly in finite samples because the tests rely on large-sample asymptotic approximations (Kerwin et al., 2024). To address this concern, we also assess joint baseline balance across the six treatment arms using a randomization inference (RI) omnibus test that replicates the actual randomization procedure. The RI p-value is 0.27, indicating no evidence of systematic imbalance in baseline covariates across treatment groups.

Table 2 presents summary statistics on post-intervention outcomes recorded for the intervention period (July 8 to September 20, 2024), including shrimp farming decisions, technology adoption, input use, and output performance, disaggregated by treatment group. The first row shows that approximately 55% of the full sample chose to farm Black-tiger shrimp during the July–September 2024 production period, with farming rates ranging from 51% to 59% across treatment arms. These differences are modest, and a formal regression of the Black-tiger farming decision on treatment indicators confirms that treatment assignment did not significantly affect the decision to farm Black-tiger (see Appendix Table F1). This supports the interpretation that subsequent differences in SPF-PL adoption are not driven by differential selection into shrimp farming.

Table 2: Post-intervention summary statistics in 2024

	Treatment Group						
Variable	**Control (1)**	**Treat 1 (2)**	**Treat 2 (3)**	**Treat 3 (4)**	**Treat 4 (5)**	**Treat 5 (6)**	**Total (7)**
1=Farmed shrimp since Jul 8, 2024	0.530 (0.501)	0.514 (0.501)	0.556 (0.498)	0.592 (0.493)	0.548 (0.499)	0.571 (0.496)	0.553 (0.497)
1=Redeemed the discount voucher (uncond.)	0.000 (0.000)	0.125 (0.332)	0.138 (0.345)	0.110 (0.314)	0.095 (0.295)	0.079 (0.270)	0.1104 (0.312)
1=Purchased Mid-grade SPF-PL (uncond.)	0.091 (0.28)	0.106 (0.308)	0.106 (0.308)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.049 (0.006)
1=Purchased Mid-grade SPF-PL (cond.)[a]	0.172 (0.380)	0.206 (0.406)	0.190 (0.395)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.088 (0.284)
1=Purchased Premium-grade SPF-PL (uncond.)	0.024 (0.155)	0.019 (0.138)	0.032 (0.176)	0.110 (0.314)	0.095 (0.295)	0.079 (0.270)	0.062 (0.241)
1=Purchased Premium-grade SPF-PL (cond.)	0.046 (0.211)	0.037 (0.191)	0.057 (0.233)	0.186 (0.391)	0.174 (0.381)	0.138 (0.346)	0.111 (0.315)
Purchased Mid-grade (numbers, uncond.)	1,226 (4,626)	866 (3,101)	1,303 (5,134)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	537 (3,044)
Purchased Mid-grade (numbers, cond.)	13,400 (8,626)	8,191 (5,652)	12,315 (10,867)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	11,009 (8,712)
Purchased Premium-grade (numbers, uncond.)	244 (2,013)	147 (1,177)	576 (3,709)	956 (3,355)	1,115 (4,712)	979 (4,591)	682 (3,528)
Purchased Premium-grade (numbers, cond.)	10,000 (9,487)	7,625 (4,423)	18,133 (11,630)	8,688 (6,011)	11,679 (10,678)	12,467 (11,513)	11,065 (9,396)
1=Purchased normal PL	0.396 (0.491)	0.370 (0.484)	0.392 (0.489)	0.431 (0.496)	0.432 (0.497)	0.455 (0.499)	0.413 (0.493)
1=Purchased normal PL on credit (cond.)	0.171 (0.382)	0.271 (0.449)	0.433 (0.504)	0.321 (0.471)	0.362 (0.486)	0.267 (0.447)	0.303 (0.460)
1=Credit available: normal/river PL (cluster-level)	0.817 (0.388)	0.875 (0.332)	0.799 (0.402)	0.858 (0.350)	0.804 (0.398)	0.880 (0.326)	0.840 (0.367)
Shrimp farming (Jul-Dec)							
Expected yield (kg) (uncond.)	62.11 (15.69)	57.39 (13.15)	65.15 (8.54)	59.42 (10.06)	63.70 (16.04)	69.26 (14.05)	62.70 (5.33)
Expected yield (kg) (cond.)	117.1 (264.6)	111.6 (253.3)	117.3 (136.9)	100.4 (182.3)	116.3 (296.1)	121.4 (244.9)	113.5 (233.0)
1=Faced shrimp mortality (uncond.)	0.128 (0.026)	0.125 (0.023)	0.148 (0.026)	0.128 (0.023)	0.136 (0.024)	0.152 (0.026)	0.136 (0.010)

Variable	Treatment Group						
	Control (1)	Treat 1 (2)	Treat 2 (3)	Treat 3 (4)	Treat 4 (5)	Treat 5 (6)	Total (7)
1=Faced shrimp mortality (cond.)	0.241 (0.430)	0.243 (0.431)	0.267 (0.444)	0.217 (0.414)	0.248 (0.434)	0.266 (0.444)	0.246 (0.431)
N	**164**	**208**	**189**	**218**	**199**	**191**	**1,169**
% of sample	**14.029**	**17.793**	**16.168**	**18.648**	**17.023**	**16.339**	**100.000**

Source: Authors' calculations.

Note: Standard deviations in parentheses. Treat 1 and Treat 2 received 100 and 50 BDT off on the 800 BDT type SPF-PL, respectively; Treat 3, Treat 4, and Treat 5 received 500, 400, and 200 BDT off on the 1200 BDT type SPF-PL, respectively. The control group only received an information card. Conditional means are conditional upon active farming shrimp during the intervention period. BDT = Bangladeshi Taka; USD 1 = BDT 122. [a]Conditional on stocking black tiger shrimp.

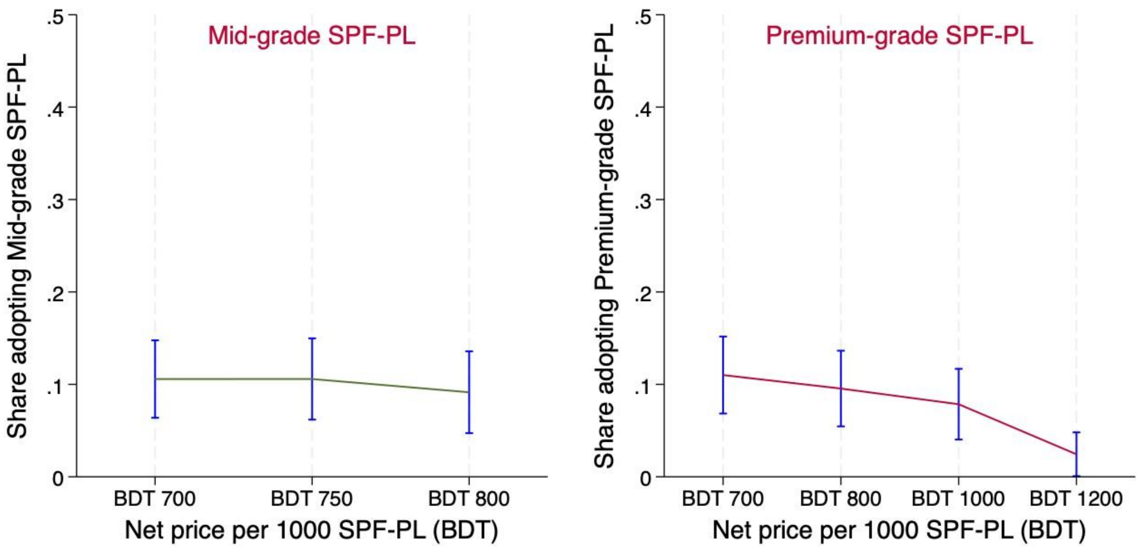
The adoption of SPF-PL in 2024 varied notably across treatment groups. Farmers in Treatment 1 and Treatment 2—who received discounts on the lower-priced Mid-grade SPF-PL (800 BDT per 1,000 PL)—exhibited higher adoption rates (both at 10.6%) relative to the control group (9.1%). No farmers in the remaining treatment groups opted to adopt Mid-grade SPF-PL. In contrast, among farmers assigned to Treatment 3 through Treatment 5—who were offered discounts on the higher-priced Premium-grade SPF-PL (1,200 BDT per 1,000 PL)—adoption rates exceeded that of the control group. While only 2.4% of farmers in the control group purchased Premium-grade SPF-PL, the corresponding rates in Treatment 3, Treatment 4, and Treatment 5 were 11.0%, 9.5%, and 7.9%, respectively. Conditional on farming Black-tiger shrimp, 4.6% control group farmers adopted Premium-grade SPF-PL, whereas adoption rates by treatment 3, 4, 5 are 18.6%, 17.4%, and 13.8%. These patterns suggest considerable price sensitivity, particularly at higher price points, which may constrain adoption even in the presence of partial subsidies—a hypothesis we examine in greater detail in the empirical analysis. Figures 5 and 6 present the relationship between price and adoption for the full sample and for the subsample of active Black-tiger shrimp farmers, respectively. In each figure, we plot the effective price of SPF-PL by type (Mid-grade in Panel A and Premium-grade in Panel B) on the x-axis, and the share of adopters on the y-axis. A negative relationship between price and adoption is evident, consistent with a downward-sloping inverse demand curve.

Among adopters, the average quantity of Mid-grade SPF-PL purchased (conditional on adoption) ranges from approximately 8,000 to 13,400, with variation across treatment groups. In contrast, the average quantity of Premium-grade SPF-PL purchased ranges from about 8,600 to 12,400 among farmers in Treatment Groups 3, 4, and 5. Notably, 2–3% of farmers in Treatment Groups 1 and 2 also purchased Premium-grade SPFPL, with average purchase volumes ranging from 7,600 to 18,000. Normal hatchery PL continues to be widely used: 41% of farmers reported purchasing it in 2024, and nearly 30% of these purchases were made on credit. Credit availability for either of the normal or river-PL was widespread: in 84% study clusters, farmers could avail these PLs on credit.

In terms of production outcomes, we recorded farmers' expected yield, gross value, mortality experience. Expected yield is derived from the question: "How much shrimp have you harvested or anticipate harvesting in your ponds, starting from the second week of July until the harvest of the latest stock? (in kg), including the stock in the pond." The average unconditional yield stands at 63 kg, while yield upon farming Black-tiger shrimp from July 2024 is around 113 kg. Notably, 25% of active Black-tiger shrimp farmers reported shrimp mortality between the intervention and the endline—a short observation window that may not capture full-season outcomes but still highlights ongoing production risks.

Figure 5: Adoption rates of Mid-grade and Premium-grade SPF-PL at different price points (full sample)

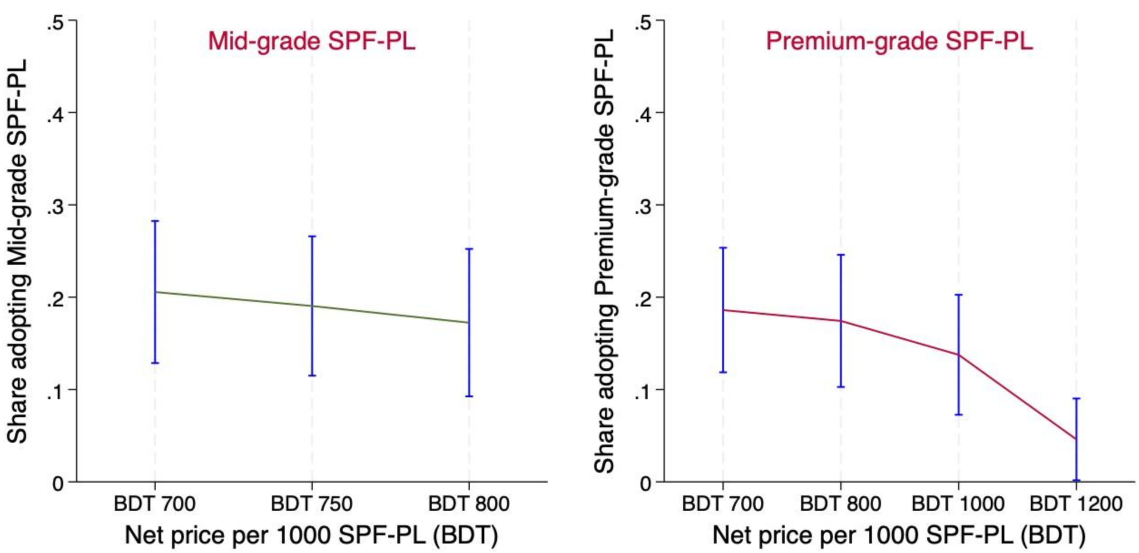
Panel A Panel B



Source: Authors' calculations.

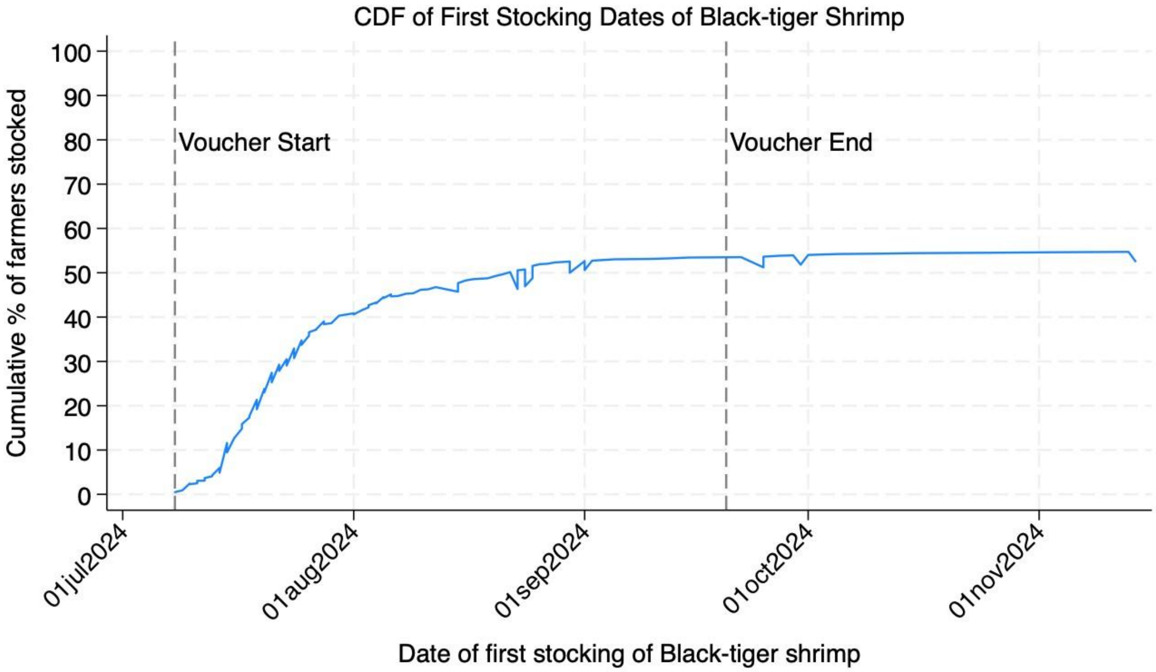
Figure 6: Adoption rates of Mid-grade and Premium-grade SPF-PL at different price points (conditional on active farming in 2024)

Panel A Panel B



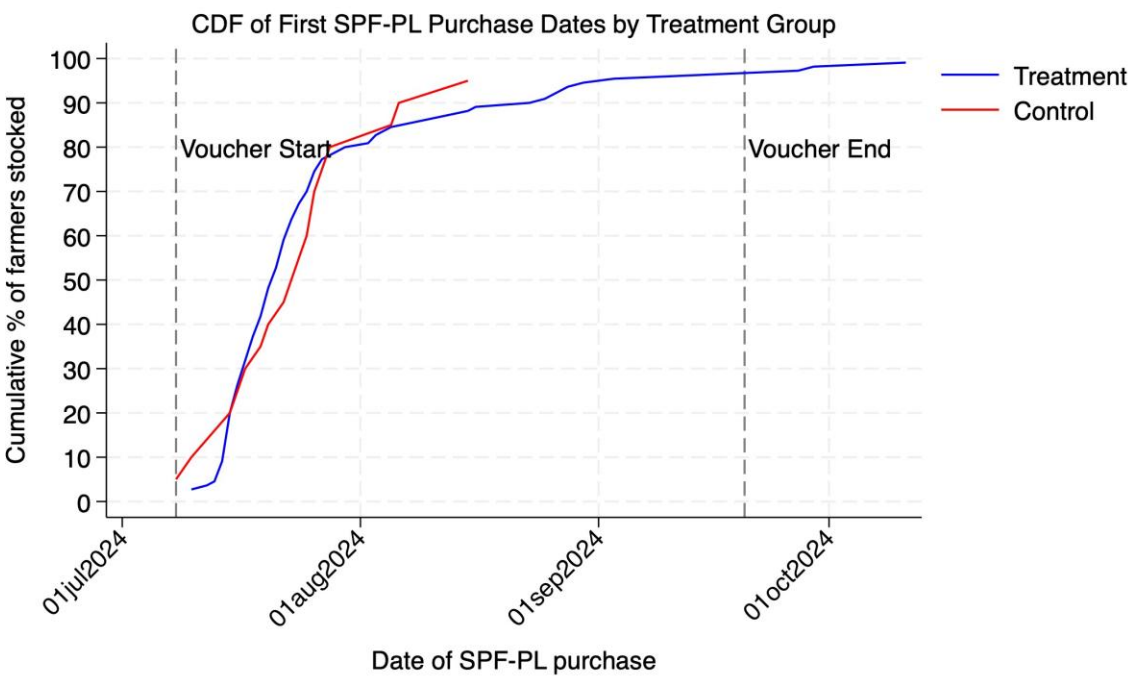
Source: Authors' calculations.

Figure 7: CDF of Black-tiger shrimp first stocking date after voucher distribution: Normal PL, SPF-PL, or River-PL



Source: Authors' calculations.

Figure 8: CDF of SPF-PL purchase date by treatment (conditional on purchasing)



Source: Authors' calculations.

Figure 7 presents the cumulative distribution of Black-tiger shrimp stocking dates, regardless of PL type, starting from the beginning of the voucher redemption period. Farmers continued to stock Black-tiger shrimp until around late September. Figure 8 shows the comparative timing of SPF-PL purchases between the control group and overall treatment status. While control group farmers stopped purchasing SPF-PL by late August, treated farmers continued purchasing until the voucher expiration date. This pattern may reflect the influence of environmental constraints—such as declining salinity or flooding—on control farmers' stocking decisions. In contrast, treated farmers may have been more incentivized to stock despite natural limitations due to the presence of the voucher.

5 CONCEPTUAL FRAMEWORK

We assume a myopic reduced-form model where a farmer decides on adopting the SPF-PL technology, or the normal hatchery PL for the immediate next stocking period, and the choice of the technology may not necessarily have a direct impact on future stocking periods through significant sunk investments. Farmer has the scope of switching back to one technology or the other if he wishes.

We assume a shrimp farming ecosystem where a shrimp farmer has two competitive technologies as alternatives. In each stocking period t, farmer i chooses between two types of post-larvae (PL) for stocking: Specific Pathogen-Free PL (S) and traditionally available normal hatchery PL (N), or a mix of the two (M). For the sake of simplicity, we drop the distinction between Mid-grade and Premium-grade SPF-PL and group the two variants as one category. Also, river-sourced PL is excluded from the analysis due to its relatively higher cost, limited market availability, and because the intervention is explicitly designed to promote SPF-PL as an alternative to the commonly used normal hatchery PL.

Let the technology choice set be denoted by $j \in S, N, M$. We denote farmer i's technology choice in stocking period t as y_{it}.

Let the utility from choosing PL type and the mix in $j \in S, N, M$ in period t be:

$$U_{ijt} = \mathbb{E}_t\left[R_{ijt} - p_{ijt} - C_j(\boldsymbol{w}_t, \boldsymbol{X}_{it}) - \tau_{ijt}\right] + \theta_i Z_{ijt} + \gamma q_j + \nu_{ijt}$$

Where:

- $\mathbb{E}_t\left[R_{ijt}\right]$: Expected revenue per thousand PL from using PL type j in period t
- p_{ijt}: Price of per thousand PL type j
- $C_j(\boldsymbol{w}_t, \boldsymbol{X}_{it})$ is a flexible cost function for other variable inputs, increasing in the vector of input prices $\boldsymbol{w}_t = (\omega_{1t}, \dots, \omega_{Kt})$ (feed, labor, lime, probiotics, etc.) and farmer/pond characteristics $\boldsymbol{X}_{it}$.
- τ_{ijt}: Non-price transaction costs (e.g., transport, credit, time, information search)
- Z_{ijt}: A vector of behavioral and perceptual factors related to a specific technology, including perceived quality, prior experience, learning from others, risk exposure, and curiosity.
- θ_i: Weight farmer i places on behavioral/perceptual factors
- q_j: Actual quality of the PL type j as advertised by the producer
- ν_{ijt}: Idiosyncratic preference shifter shock (captures unobserved idiosyncratic preferences for PL type j, assumed to be mean-zero and i.i.d. across individuals and options.)

The farmer's decision is then given by:

$$y_{it} = \arg \max_{j \in \{S,N,M\}} U_{ijt} \tag{1}$$

We define the effective price for each choice $j \in S, N, M$ as:

$$p_{ijt}^{\text{eff}} = p_{ijt} - d_{ijt}$$

where:

$$d_{ijt} = \begin{cases} d_{it}, & if\ j = S \\ 0, & if\ j = N \\ \alpha_i^S \cdot d_{it}, & if\ j = M \end{cases}$$

and $\alpha_i^S \epsilon (0,1)$ denotes the share of SPF-PL used in the mix. That is, the mix option receives a partial discount proportional to the SPF-PL share.

Our randomized assignments introduces a variation in d_{ijt}.The introduction of the discount voucher d_{ijt} for SPF-PL (i.e., for $j = S$) directly lowers the effective price paid by the farmer, thus increasing the farmer's net utility from choosing SPF-PL relative to the other available options. From the utility function:

$$U_{ijt} = \mathbb{E}_t\big[R_{ijt} - (p_{ijt} - d_{ijt}\big) - C_j(\boldsymbol{w}_t, \boldsymbol{X}_{it}) - \tau_{ijt}] + \theta_i Z_{ijt} + \gamma q_j + \nu_{ijt},$$

We see that an increase in d_{ijt} (i.e., a higher discount) increases U_{ijt} for $j = S$ by reducing the effective price. Holding expectations of returns R_{ijt}, transaction costs τ_{ijt}, and observable and unobservable non-price factors constant, this price discount mechanically increases the attractiveness of SPF-PL.

Therefore, the model predicts that, *ceteris paribus*, farmers should be more likely to adopt SPF-PL when offered a higher voucher amount. This theoretical prediction constitutes the core hypothesis of our study: if economic incentives matter, then lowering the relative cost of SPF-PL through randomized discounts should increase its adoption. The empirical strategy tests whether this predicted behavioral response—shifting demand toward a subsidized, higher-quality technology—is realized in practice under real-world production and market constraints.

Finally, the farmer solves the optimization problem shown in Equation (1) given the availability of the discounted SPF-PL.

Our experimental design allows us to estimate the causal effect of price discounts on the adoption of Mid-grade and Premium-grade SPF-PL—two variants that differ in quality q —through a randomized intervention. The survey data further enable us to examine how variation in treatment groups interacts with behavioral and perceptual factors shaped by prior farming practices, and explains the mechanism behind adoption behavior. In this framework, we conceptualize the following variables as behavioral factors, denoted by Z_{ijt}:

- **Experience through prior exposure:** Farmers previously exposed to the technology through first-hand use, information acquisition, or training may have already formed beliefs or preferences, affecting their responsiveness to new information or incentives. This behavior reflects experience-based learning in technology adoption (Conley and Udry, 2010; Foster and Rosenzweig, 1995). In our model, previous SPF-PL usage through participation in multi-actor intervention program in 2023 serves as the variable on prior exposure.

- **Reference dependence and anchoring effect:** Farmers may form reference-dependent preferences by anchoring their current price expectations to previously experienced prices, particularly if those prior experiences involved receiving a product for free. In such cases, the perceived utility from purchasing the same product—even at a discounted price—can be diminished if the current price exceeds the reference point established during the free distribution. This behavioral response is consistent with models of reference-dependent utility, where past prices act as anchors shaping subsequent willingness to pay (Köszegi and Rabin, 2006), whereas the absence of it is also possible (Dupas, 2014).

  In the context of our study, the multi-actor intervention program involved the free—albeit nonrandomized— distribution of Mid-grade SPF-PL to a subset of farmers during the baseline cycle. This setting provides a unique opportunity to test whether prior receipt of free Mid-grade SPF-PL is correlated with adoption behavior in the presence of a new price-based incentive (i.e., discount vouchers). If reference dependence is operative, we would expect lower responsiveness to vouchers among farmers who previously received SPF-PL at no cost.

- **Risk experience and mitigation behavior:** This behavioral factor captures response due to prior-cycle shrimp mortality or adverse production shocks. This captures a potential risk-salience effect, where recent exposure to negative shocks increases the perceived value of risk-mitigating technologies (Kahneman and Tversky, 1979; Cole et al., 2013). In our model, farmer who experienced losses due to diseases may be more inclined to adopt technologies perceived to offer the disease-free feature. Conversely, recent exposure to a natural disaster may impose capital constraints that deter farmers from adopting new technologies (Carter and Barrett, 2006).

- **Infrastructure preparedness:** Forward-looking farmers may undertake productive investments that signal their confidence in aquaculture returns and their capacity to invest in new technology. Observable infrastructure such as the presence of a nursing facility can proxy for unmeasured traits such as optimism, liquidity, preparedness, all of which are theorized to influence technology adoption decisions (Dercon and Christiaensen, 2011). In the context of shrimp farming, establishing a nursing area—typically a semi-secluded section of the pond or a separate nursery tank used to raise PLs during their early stages—is considered a good aquaculture practice aimed at improving survival rates and reducing early-stage mortality. If a farmer has a nursing facility, it may positively influence their willingness to adopt SPF-PL, as nursing is particularly a recommended practice for effectively cultivating SPF-PL.

6 EMPIRICAL STRATEGY

6.1 Main specification

We varied both the price level (via discount size) and the type of PL offered through the discount (Mid-grade SPF-PL: 800 BDT vs. Premium-grade SPF-PL: 1200 BDT). A core objective of our experimental design is to assess how price incentives and product quality interact to influence adoption behavior. To estimate the causal impact of these vouchers on outcomes by type, we present two separate specifications aligned with the experimental design. Since the two PL types differ in both market price and advertised quality—and each set of vouchers were specific to PL type—our approach allows for a disaggregated analysis of treatment effects.

We first estimate the intention-to-treat (ITT) effects of the vouchers for Mid-grade SPF-PL (Treatment groups 1 and 2) using the following model:

$$Y_{i_{Midgrade}} = \alpha + \sum_{k=1}^{2} \beta_{k_{Midgrade}} T_{ki} + \phi_1 Y_i^{baseline} + \phi_2 Flood_i^{2024} + \phi_3 DistanceToCity_i + X_i' \theta_1 + \theta_2 SampleType_i + \lambda_{cluster} + \varepsilon_i \tag{2}$$

Also, we estimate the effects of the vouchers for Premium-grade SPF-PL (Treatment groups 3 to 5) separately using:

$$Y_{i_{Premium}} = \alpha + \sum_{k=3}^{5} \beta_{k_{Premium}} T_{ki} + \phi_1 Y_i^{baseline} + \phi_2 Flood_i^{2024} + \phi_3 DistanceToCity_i + X_i' \theta_1 + \theta_2 SampleType_i + \lambda_{cluster} + \varepsilon_i \tag{3}$$

These specifications allow us to estimate how adoption varies across combinations of price and quality, providing insight into farmers' responsiveness to economically and qualitatively differentiated inputs.

In both equations 2 and 3, $Y_{i_{Midgrade}}$ and $Y_{i_{Premium}}$ denote the outcome variable for farmer i by type of SPF-PL, and T_{ki} represents treatment group indicators for Treatment groups 1 and 2 for equation 2 and Treatment groups 3 to 5 for equation 3 (with the control group as the omitted reference category). The term $Y_i^{baseline}$ controls for the baseline value of the outcome under an ANCOVA specification as failing to control for the baseline value of the outcome induces finite-sample bias (Kerwin, 2025).

Although treatment assignment was randomized at the individual level, farmer sampling was first done at the cluster level. Clusters may differ in unobserved ways—such as local water salinity, historical disease prevalence, proximity to roads and markets, influence of local extension agents, or prevailing social norms—that could affect outcomes. To account for these time-invariant, cluster-specific factors, we include cluster fixed effects $\lambda_{cluster}$, which also absorb all between-cluster variation.

We additionally control for the type of sample—the second stage of the sampling procedure, represented by $SampleType_i$, where values indicate (1) 2023 intervention-participant farmers, (2) non-participant farmers in the same village, and (3) non-participant farmers in adjacent villages. The variable $Flood_i^{2024}$ captures self-reported exposure to the August 2024 flooding event, which coincided with the intervention. To address disruptions caused by political unrest in Khulna city, we include $DistanceToCity_i$, the farm's distance from Khulna city center.

We use Least Absolute Shrinkage and Selection Operator (LASSO) that selects a subset of variables from a range of high-dimensional potential covariates by forcing some coefficients to zero. The vector Xi includes these additional covariates selected through LASSO to avoid overfitting (Belloni et al., 2014), and ε_i is the error term. Standard errors are clustered at the cluster level to account for intra-cluster correlation (Abadie et al., 2022).

In these specifications, we use Ordinary Least Squares (OLS) to estimate ITT effects for both the full sample and the subsample of farmers who chose to farm Black-tiger shrimp during the July–September study period, since SPF-PL adoption is only relevant for Black-tiger shrimp cultivation. Importantly, Appendix Table F1 shows no statistically significant association between treatment assignment and the decision to farm Black-tiger shrimp, suggesting that selection into farming was not systematically driven by the differential discount treatment and can be treated as exogenous.[8] Given the limited sample size of 646 active shrimp farmers, statistical power may be constrained, and as such, the estimated effects for this subgroup should be interpreted with caution.

As our primary outcome variable across all specifications, we focus on short-term adoption behavior, measured at the extensive margins. The extensive margin is captured by a binary indicator for whether the farmer stocked SPF-PL during the July–September 2024 production cycle. Understanding this adoption behavior is the central objective of the study. Note that not all farmers harvested when we completed our endline survey as it typically requires 3-4 months to harvest, but we were able to capture the expected yield and mortality experience through our survey. Therefore, for the active farmers, we also examine two additional outcome variables: (i) expected yield (in kilograms), based on realized or anticipated harvest from shrimp farming, and (ii) a binary indicator of shrimp mortality experience prior to the survey date in equations 2 and 3. For these two outcomes, we control for the date of the most recent stocking to account for variation in production timelines.

The coefficients of interest in equations 2 and 3 are the β's, which measure the effect of the voucher treatment relative to the control group. We hypothesize these to be positive for all these three outcomes.

For the two second- order outcomes –expected yield (in kilograms) and the binary indicator of shrimp mortality experience—we also estimate the Local Average Treatment Effects (LATE), conditional on adoption (i.e., satisfying the first stage):

$$SecondStageOutcome_i = \alpha + \rho_1 \hat{Y}_i^{(1)} + \phi_1 Y_i^{baseline} + \phi_2 Flood_i^{2024} + \phi_3 DistanceToCity_i X_i' \theta_1 + \theta_2 SampleType_i + \lambda_{cluster} + \nu_i \quad (4)$$

where $\hat{Y}_i^{(1)}$ is the predicted value from the first stage equations such as 2 or 3. In equation 4, coefficient ρ is the LATE estimate, hypothesized to be positive for the two outcomes.

[8] We find that the August 2024 flood significantly influenced farmers' decisions to cultivate Bagda shrimp. Appendix Table G1 reports the simple regression results. Among farmers who had not yet initiated farming by August 21, 2024—the day the flood occurred—those affected by the flood were 9 percentage points less likely ($p < 0.01$) to farm Bagda compared with unaffected farmers. Descriptively, among the 598 farmers who had not begun farming by August 21, 58.7% chose not to farm Bagda for the remainder of the year.

6.2 Understanding the mechanism behind adoption: Heterogeneity analysis

To examine the mechanism behind the adoption behavior, we estimate heterogeneous treatment effects by interacting the treatment variable with relevant subgroup indicators to understand the mechanism of adoption-behavior by the farmers. We use the following model in equation 5 and 6:

$$Y_{i_{Midgrade}} = \beta_0 + \sum_{k=1}^{2} \beta_{k_{Midgrade}} T_{ki} + \gamma Z_i + \sum_{j=1}^{2} \delta_{j_{Midgrade}} \left(T_{k,i} \cdot Z_i\right) + \phi_1 Y_i^{baseline} + \phi_2 Flood_i^{2024} + \phi_3 DistanceToCity_i + X_i' \theta_1 + \theta_2 SampleType_i + \lambda_{cluster} + \varepsilon_i \quad (5)$$

and

$$Y_{i_{Premium}} = \beta_0 + \sum_{k=3}^{5} \beta_{k_{Premium}} T_{ki} + \gamma Z_i + \sum_{j=3}^{5} \delta_{j_{Premium}} \left(T_{k,i} \cdot Z_i\right) + \phi_1 Y_i^{baseline} + \theta_2 Flood_i^{2024} + \theta_3 DistanceToCity_i + X_i' \theta_1 + \theta_2 SampleType_i + \lambda_{cluster} + \varepsilon_i \quad (6)$$

where Z_i is the variable interacted with the treatment variable for individual i. Z_i represents the behavioral and perceptual factors that could affect farmers adoption behavior. Equations 5 and 6 allow us to test for heterogeneous treatment effects along five hypothesized dimensions of farmer behavior, consistent with the pathways outlined in our conceptual framework:

- **Experience through prior exposure.** In our sample, about 50% farmers participated in the multi-actor intervention program. We hypothesize that farmers who previously participated in this intervention in 2023 may have developed stronger beliefs—positive or negative—about the promoted technology based on prior exposure. We use a binary variable equal to 1 if the farmer participated in the multi-actor intervention program. The decision for a farmer to participate in the multi-actor intervention program was primarily determined by the cluster organizers—namely, the DoF, ACI Agrolink, or BSFF.

- **Reference dependence and anchoring effects:** Among farmers in who participated in the multi-actor intervention program, 20.4% reported receiving free Mid-grade SPF-PL in the previous year. We hypothesize that these farmers may anchor their expectations to a zero-price benchmark and perceive the discounted (but nonzero) prices in our intervention as unfavorable. To test this, we define a binary indicator equal to 1 if the farmer received SPF-PL for free in 2023, regardless of quantity. One might interpret the receipt of free SPF-PL as plausibly exogenous, given that its allocation was solely determined by cluster organizers and not part of our experimental intervention. However, the receipt of free SPF-PL might also be endogenous to unobservables (e.g., timing of the formation of cluster, farmer ability, network access of the cluster etc.). Hence, we are not using it as a causal mediator, but rather as an interacting or moderating variable in heterogeneity analysis.

- **Risk-experience and mitigation behavior:** We define a binary indicator for whether the farmer experienced shrimp mortality in 2023. Notably, 68% farmers reported experiencing mortality in the pond. We hypothesize that past mortality may trigger risk-mitigation behavior, increasing demand for SPF-PL given its purported ability to reduce disease risks. Further, 29.3% farmers reported to be affected by cyclone in May 2024, two months prior to the experiment. By interacting the treatment variables with self-reported exposure to the cyclone that occurred two months prior to the intervention, we test the hypothesis that such exposure reduces the capacity to invest in technologies such as SPF-PL.

- **Infrastructure preparedness:** Finally, we test whether technology-supportive investment affects adoption by including a binary variable equal to 1 if the farmer had a nursing facility in 2023. About 37% of the farmers reported undertaking this investment. Our hypothesis is that recent capital expenditure may influence adoption behavior: it may signal higher expected returns and thus increase responsiveness to quality-enhancing inputs such as SPF-PL.

7 RESULTS

7.1 Effects of the discount vouchers on adoption behavior

We begin by examining whether discount vouchers influenced the adoption of Specific Pathogen Free post-larvae (SPF-PL). Table 3 presents the intention-to-treat (ITT) estimates for Mid-grade SPF-PL adoption, covering both the full sample and the subsample of farmers who actively farmed shrimp between the intervention rollout (July 8, 2024) and the voucher expiration (September 20, 2024).

Across both samples, we find no statistically significant effect of voucher assignment on adoption, expected yield or mortality experience. In the full sample, the estimated treatment effect on binary adoption is 0.026 (s.e. = 0.033), while in the active farmer subsample it is 0.065 (s.e. = 0.062). Neither estimate is statistically distinguishable from zero. We also find no significant effects on expected yield or expected mortality.

Table 4 reports ITT estimates for Premium-grade SPF-PL adoption, which was targeted by treatment groups 3 through 5. Unlike the case of Mid-grade, all treatment effects for Premium-grade are statistically significant at the extensive margin. In the full sample, assignment to Treatment 3, 4, and 5 increases the likelihood of adoption by 10.0 percentage points ($p < 0.01$), 7.9 percentage points ($p < 0.05$), and 6.3 percentage points ($p < 0.05$), respectively, compared to the control group. Among active farmers, these effects are larger in magnitude: 18.8 ($p < 0.01$), 14.2 ($p < 0.05$), and 10.0 ($p < 0.05$) percentage points, respectively. Benjamini–Hochberg Adjusted P-values for Multiple Hypothesis Tests are reported in Appendix Table H1.

Interestingly, although Treatment 3 offered the highest discount and yielded the largest effect, pairwise coefficient equality tests do not reject the null that these effects are statistically different from one another. This suggests diminishing marginal returns to increasing discounts, implying that a lower discount (e.g., BDT 200) may be sufficient to induce adoption and thus, more cost-effective.

These contrasting results between Mid-grade and Premium-grade SPF-PL adoption impact are informative. The lack of effect for Mid-grade may reflect diminishing returns to financial incentives in contexts where prior exposure is high. Notably, the 2023 multi-actor campaign led by the Department of Fisheries, ACI Agrolink, and the Bangladesh Shrimp and Fish Foundation had already promoted Mid-grade SPF-PL extensively. Therefore, the absence of an effect even under large price discounts may point to other adoption barriers—such as risk perceptions, learning thresholds, or perceived quality differences—that are not alleviated by subsidies alone.

By contrast, the consistently positive and significant ITT effects for Premium-grade SPFPL suggest that price remains a key barrier to adopting higher-quality inputs. These results underscore the potential complementarity between quality improvements and affordability. The finding that even modest discounts lead to measurable adoption gains supports the hypothesis that perceived quality plays a pivotal role in technology take-up.

Among active farmers, however, we find no conclusive short-term ITT effects on yield or mortality for either type (column (3) and (4)), additionally controlling for the date of last stocking. This could be due to the short follow-up period or the ex-ante uncertainty in actual biological outcomes.

We complement the ITT analysis by estimating the local average treatment effect (LATE) of adopting Premium-grade SPF-PL, using randomized treatment assignment as an instrument. To estimate the LATE, we instrument actual adoption with randomized treatment assignment. This approach relies on standard instrumental variable assumptions: (i) the exclusion restriction—that the instrument affects outcomes only through adoption; (ii) monotonicity—that discount treatment assignment does not induce adoption defiers; and (iii) relevance—evidenced by strong first-stage estimates (see Table 5). While the first two assumptions are not directly testable, the experimental design and context lend credibility to the identification strategy.

Among active farmers, we find no effect on yield and expected mortality. The absence of significant effects on expected yield or shrimp mortality may reflect the short duration between stocking and survey administration. Since harvesting was incomplete for many respondents at the time of data collection, farmers' expectations may not yet align with realized outcomes. We interpret these results with caution.

We now turn to the potential mechanisms behind observed adoption patterns. Specifically, we analyze heterogeneity by prior exposure, experience with SPF-PL, recent shrimp mortality, and investment behaviors such as having a nursing facility. These behavioral and contextual moderators may explain why treatment effects are stronger in some Premium-grade SPF-PL adoption behavior and muted in the Mid-grade SPF-PL.

Table 3: Impact of discount vouchers on Mid-grade SPF-PL adoption, expected yield, and expected mortality (full sample and Active farmers): Intention-to-treat (ITT) effects

	Adoption of Mid-grade SPF-PL (1/0)		Expected yield (kg)	Experienced mortality (1/0)
	(1)	(2)	(3)	(4)
Variable	Full Sample	Active Shrimp Farmers	Active Shrimp Farmers	Active Shrimp Farmers
Treatment 1: 100 taka off from BDT 800 type	0.026 (0.033)	0.065 (0.062)	33.123 (29.594)	0.042 (0.069)
Treatment 2: 50 taka off from BDT 800 type	0.028 (0.045)	0.039 (0.089)	32.256 (27.083)	0.023 (0.079)
Farm flooded in Aug 2024 (1/0)	-0.056* (0.033)	-0.074 (0.066)	-34.273 (36.259)	0.006 (0.110)
Distance to Khulna (in km)	0.001 (0.015)	-0.011 (0.058)	13.426 (23.229)	0.000 (0.059)
Outcome in baseline	0.094 (0.085)	0.168 (0.181)	0.080 (0.196)	0.034 (0.077)

Variable	Adoption of Mid-grade SPF-PL (1/0) (1) Full Sample	(2) Active Shrimp Farmers	Expected yield (kg) (3) Active Shrimp Farmers	Experienced mortality (1/0) (4) Active Shrimp Farmers
Constant	-0.120 (0.892)	0.548 (3.496)	-1,273.030 (5,106.219)	7.667 (12.854)
Treatment 1 = Treatment 2 (p-value)	0.9621	0.7307	0.9772	0.7769
Control group: Dependent variable mean	0.091	0.172	117.081	0.241
Control group: Dependent variable SD	(0.289)	(0.380)	(264.599)	(0.430)
Observations	561	299	299	299
R-squared	0.237	0.318	0.507	0.391
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Sample-type Fixed Effects	Yes	Yes	Yes	Yes
LASSO-picked controls	Yes	Yes	Yes	Yes

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. All regressions use clustered standard errors at the cluster level. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 4: Impact of discount vouchers on Premium-grade SPF-PL adoption, expected yield, and mortality: Full sample and Active farmers

Variable	Adoption of Mid-grade SPF-PL (1/0) (1) Full Sample	(2) Active Shrimp Farmers	Expected yield (kg) (3) Active Shrimp Farmers	Experienced mortality (1/0) (4) Active Shrimp Farmers
Treatment 3: BDT 500 off from BDT 1200 type	0.100*** (0.023)	0.188*** (0.051)	30.974 (23.861)	0.004 (0.060)
Treatment 4: BDT 400 off from BDT 1200 type	0.079** (0.030)	0.142** (0.067)	33.116 (41.281)	0.070 (0.065)
Treatment 5: BDT 200 off from BDT 1200 type	0.063** (0.026)	0.100** (0.046)	24.827 (21.012)	0.000 (0.083)
Farm flooded in August 2024	0.000 (0.023)	-0.029 (0.038)	-40.832 (28.519)	0.046 (0.056)
Distance to Khulna (in km)	0.004 (0.019)	-0.012 (0.040)	13.022 (8.233)	-0.013 (0.038)
Date of last stocking	-	-	-0.059 (0.149)	0.000 (0.001)
Outcome in baseline	0.054 (0.164)	0.466 (0.351)	0.213 (0.233)	-0.066 (0.060)
Constant	-0.323	0.631	555.713	0.956

Variable	Adoption of Mid-grade SPF-PL (1/0)		Expected yield (kg)	Experienced mortality (1/0)
	(1)	(2)	(3)	(4)
	Full Sample	Active Shrimp Farmers	Active Shrimp Farmers	Active Shrimp Farmers
	(1.126)	(2.300)	(3,574.914)	(16.008)
Control group: Dependent variable mean	0.024	0.046	117.081	0.241
Control group: Dependent variable SD	(0.155)	(0.211)	(264.599)	(0.430)
Treatment 3 = Treatment 4 (p-value)	0.5027	0.3913	0.9514	0.2424
Treatment 4 = Treatment 5 (p-value)	0.6537	0.5449	0.8376	0.3273
Treatment 3 = Treatment 5 (p-value)	0.2496	0.1307	0.7819	0.9642
Observations	772	434	434	434
R-squared	0.135	0.272	0.349	0.353
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Sample-type Fixed Effects	Yes	Yes	Yes	Yes
LASSO-picked controls	Yes	Yes	Yes	Yes

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the cluster level. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 5: LATE Estimates of Premium-grade SPF-PL Adoption on Expected Yield and Mortality (Active Farmers Only)

	(1) Expected yield (kg)	(2) Expected mortality (1/0)
	Active Farmers	Active Farmers
Panel A: Second Stage (LATE)		
Farmer adopted Premium-grade SPF-PL in 2024 (1/0)	199.687 (126.773)	0.018 (0.306)
Farm flooded in August 2024 (1/0)	-40.612 (26.631)	0.058 (0.049)
Distance to Khulna (in km)	6.888 (12.127)	-0.006 (0.035)
Outcome in baseline	0.372 (0.210)	-0.042 (0.053)
Date of last stocking	0.082 (0.249)	0.000 (0.001)
Control group: Dependent variable mean	117.081	0.241
Control group: Dependent variable SD	(264.599)	(0.430)
Observations	434	434

	(1) Expected yield (kg)	(2) Expected mortality (1/0)
	Active Farmers	Active Farmers
R-squared	0.224	0.346
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes
	Adoption of Premium-grade (1/0)	
	Active Farmers	Active Farmers
Panel B: First Stage (Instrument = Voucher Assignment)		
Treatment 3: BDT 500 off from BDT 1200 type	0.185*** (0.051)	0.185*** (0.051)
Treatment 4: BDT 400 off from BDT 1200 type	0.144** (0.064)	0.144** (0.064)
Treatment 5: BDT 200 off from BDT 1200 type	0.121*** (0.044)	0.121*** (0.044)

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. The second stage reports the Local Average Treatment Effect (LATE) of adopting Premium-grade SPF-PL on yield and mortality. The first stage estimates the effect of voucher assignment (Treatment 3 to Treatment 5) on adoption. For regression (1), LASSO-picked control is whether the pond was deepened in 2023, for regression in (2), LASSO-picked controls are: local availability of SPF-PL before the intervention and whether farm was affected by cyclone.

7.1.1 Mechanism behind adoption behavior: Heterogeneous treatment effects

(i) Experience effects through prior multi-actor intervention participation

We begin by examining whether prior exposure to SPF-PL through the 2023 multi-actor intervention shaped farmers' responsiveness to the discount vouchers. Table 6 presents estimates of the treatment effects interacted with 2023 intervention-participation. Columns (1) and (2) report effects on the extensive margin, for the full sample and active farmers, respectively. For Mid-grade, we find evidence of negative experience effects. Specifically, farmers in treatment group 2 (BDT 50 discount) who previously participated in the multi-actor intervention are 10.4 percentage points less likely to adopt Mid-grade SPFPL compared to non-participants in the same treatment group ($p < 0.05$). For treatment group 1 (BDT 100 discount), the interaction term is also negative across both samples, though not statistically significant. Similarly, in the subsample of active farmers, the point estimates remain negative but are not statistically significant.

Taken together, these findings for Mid-grade SPF-PL point toward a plausible negative experience effect, although the evidence is statistically significant only in select specifications: farmers previously exposed to SPF-PL through the intervention appear less responsive to the price discount. This result is notable given that prior intervention participation was designed to promote informed and sustained uptake of SPF-PL, with specific logistical support for Mid-grade SPF-PL. A possible interpretation is that these farmers—despite receiving training and information on the technology—might not experience the expected improvements in yield or disease resistance during the prior cycle. These dynamics may also warrant further investigation into behavioral mechanisms, particularly reference dependence through anchoring to previously experienced prices, which we explore in the following section.

For Premium-grade SPF-PL (see Table 7), the experience effects move in the opposite direction. Among active farmers, those in treatment group 3 (BDT 500 discount) who previously participated in the intervention program are 19 percentage points more likely to adopt SPF-PL compared to their non-participant counterparts. This suggests that prior exposure to training, when combined with a substantial price discount on a higherquality input, may reinforce adoption behavior. While the interaction terms for other treatment groups follow a similar pattern, they are not statistically significant. However, the findings from this table suggest that farmers in our context do not exhibit lower openness to adopting new technologies, despite their lack of prior non-experience with Premium-grade.

Table 6: Heterogeneous Impact of Discount Vouchers on Mid-grade SPF-PL Adoption by Prior Participation in the 2023 Multi-Actor Intervention

	Adoption of Mid-grade SPF-PL (1/0)	
Variables	**(1) Full Sample**	**(2) Active Farmers**
Treatment 1: BDT 100 off from BDT 800 type	0.064 (0.044)	0.113 (0.087)
Treatment 2: BDT 50 off from BDT 800 type	0.080 (0.055)	0.131 (0.128)
Multi-actor intervention participant in 2023	0.067 (0.046)	0.051 (0.102)
Treatment 1 x multi-actor intervention participation	-0.075 (0.066)	-0.077 (0.119)
Treatment 2 x multi-actor intervention participation	-0.104** (0.052)	-0.162 (0.121)
Farm affected by flood in August 2024 (1/0)	-0.054* (0.032)	-0.077 (0.064)
Distance to Khulna (in km)	0.001 (0.014)	-0.018 (0.056)
Adoption of Mid-grade SPF-PL in 2023 (1/0)	0.098 (0.087)	0.171 (0.188)
Constant	-0.172 (0.834)	0.946 (3.371)
Control group: Dependent variable mean	0.091	0.172
Control group: Dependent variable SD	(0.289)	(0.380)
Treatment 1 Mean (for non-participants in intervention)	0.087	0.170
Treatment 1 SD (for non-participants in intervention)	(0.283)	(0.379)
Treatment 2 Mean (for non-participants in intervention)	0.093	0.186
Treatment 2 SD (for non-participants in intervention)	(0.292)	(0.394)
Observations	561	299
R-squared	0.241	0.323

Variables	Adoption of Mid-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the cluster level. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 7: Heterogeneous Impact of Discount Vouchers on Premium-grade SPF-PL Adoption by Prior Participation in the 2023 Multi-Actor Intervention

Variables	Adoption of Mid-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment 3: BDT 500 off from BDT 1200 type	0.084*** (0.030)	0.150** (0.060)
Treatment 4: BDT 400 off from BDT 1200 type	0.054 (0.032)	0.064 (0.091)
Treatment 5: BDT 200 off from BDT 1200 type	0.040 (0.030)	-0.013 (0.052)
Multi-actor intervention participant in 2023	0.007 (0.032)	-0.088 (0.075)
Treatment 3 x Multi-actor intervention participant	0.045 (0.054)	0.193** (0.090)
Treatment 4 x Multi-actor intervention participant	0.050 (0.056)	0.138 (0.127)
Treatment 5 x Multi-actor intervention participant	0.032 (0.043)	0.064 (0.069)
Farm affected by flood in August 2024 (1/0)	-0.002 (0.024)	-0.034 (0.038)
Distance to Khulna (in km)	0.005 (0.020)	-0.008 (0.043)
Adoption of Premium-grade SPF-PL in 2023 (1/0)	0.053 (0.166)	0.493 (0.321)
Constant	-0.378 (1.177)	0.434 (2.486)
Control group: Dependent variable mean	0.024	0.046
Control group: Dependent variable SD	(0.155)	(0.211)
Treatment 3 Mean (for non-participants in intervention)	0.088	0.167
Treatment 3 SD (for non-participants in intervention)	(0.285)	(0.376)

Variables	Adoption of Mid-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment 4 Mean (for non-participants in intervention)	0.071	0.143
Treatment 4 SD (for non-participants in intervention)	(0.258)	(0.354)
Treatment 5 Mean (for non-participants in intervention)	0.044	0.087
Treatment 5 SD (for non-participants in intervention)	(0.206)	(0.285)
Observations	772	434
R-squared	0.136	0.280
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the cluster level. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

(ii) Reference dependence and anchoring effects

Next, we examine whether prior receipt of free Mid-grade SPF-PL under the 2023 multi-actor intervention program created a reference point that shaped subsequent adoption decisions when the product was discounted but not free. Approximately 20.4% of farmers in our sample reported receiving free Mid-grade SPF-PL in the previous year. Following the behavioral economics literature on reference dependence and anchoring to prior prices (Dupas, 2014; Köszegi and Rabin, 2006), we interact our treatment variables with a binary indicator for past receipt of free Mid-grade SPF-PL. Table 8 and Table 9 present estimates of the interaction between treatment assignment and receipt of free Mid-grade SPF-PL in the previous season, for Mid-grade and Premium-grade adoption outcomes in 2024, respectively. While the evidence is not uniformly strong, we observe suggestive patterns consistent with anchoring effects in the case of Mid-grade adoption. Specifically, farmers in treatment group 2 who previously received free Mid-grade SPF-PL are 12.6 and 20.1 percentage points less likely to adopt, relative to those in the same treatment group who did not receive the input for free. Given that treatment group 2 received the smallest price discount (BDT 50), Mid-grade SPF-PL remained relatively expensive for them, potentially amplifying the anchoring effect and discouraging purchase at the discounted price.

We next examine whether receiving Mid-grade SPF-PL for free influences adoption of Premium-grade SPF-PL. As shown in Table 9, none of the interaction terms are statistically significant. One possible explanation is that farmers—including those who received Mid-grade SPF-PL for free—are aware of the superior quality of Premium-grade SPF-PL. As such, prior exposure to the lower-quality variant at no cost may not have distorted their valuation of the higher-quality input, leaving their Premium-grade adoption decisions unaffected.

Table 8: Heterogeneous Impact of Discount Vouchers on Mid-grade SPF-PL Adoption by Prior Free Receipt of Mid-grade SPF-PL

Variables	Adoption of Mid-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment 1: BDT 100 off BDT 800 type	0.027 (0.031)	0.059 (0.065)
Treatment 2: BDT 50 off BDT 800 type	0.056 (0.044)	0.094 (0.090)
Received free Mid-grade SPF-PL in 2023 (1/0)	0.058 (0.114)	0.058 (0.216)
Treatment 1 x Received free Mid-grade SPF-PL	0.010 (0.086)	0.043 (0.159)
Treatment 2 x Received free Mid-grade SPF-PL	-0.126* (0.069)	-0.201* (0.116)
Farm affected by flood in August 2024 (1/0)	-0.059* (0.032)	-0.086 (0.065)
Distance to Khulna (in km)	0.002 (0.015)	-0.012 (0.057)
Adoption of Mid-grade SPF-PL in 2023 (1/0)	0.094 (0.085)	0.155 (0.180)
Constant	-0.160 (0.876)	0.573 (3.456)
Control group: Dependent variable mean	0.091	0.172
Control group: Dependent variable SD	(0.289)	(0.380)
Treatment 1 Mean (Free-PL non-recipient)	0.079	0.163
Treatment 1 SD (Free-PL non-recipient)	(0.270)	(0.371)
Treatment 2 Mean (Free-PL non-recipient)	0.107	0.205
Treatment 2 SD (Free-PL non-recipient)	(0.310)	(0.406)
Observations	561	299
R-squared	0.243	0.329
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 9: Heterogeneous Impact of Discount Vouchers on Premium-grade SPF-PL Adoption by Prior Free Receipt of Mid-grade SPF-PL

	Adoption of Premium-grade SPF-PL (1/0)	
Variables	(1) Full Sample	(2) Active Farmers
Treatment 3: BDT 500 off BDT 1200 type	0.117*** (0.029)	0.216*** (0.063)
Treatment 4: BDT 400 off BDT 1200 type	0.079** (0.034)	0.152* (0.080)
Treatment 5: BDT 200 off BDT 1200 type	0.065** (0.027)	0.094* (0.053)
Received free Mid-grade SPF-PL in 2023 (1/0)	0.002 (0.053)	-0.067 (0.095)
Treatment 3 x Received free Mid-grade SPF-PL	-0.072 (0.047)	-0.110 (0.095)
Treatment 4 x Received free Mid-grade SPF-PL	0.006 (0.058)	-0.034 (0.133)
Treatment 5 x Received free Mid-grade SPF-PL	-0.005 (0.080)	0.032 (0.106)
Farm flooded in Aug 2024 (1/0)	0.001 (0.024)	-0.028 (0.039)
Distance to Khulna (in km)	0.004 (0.020)	-0.012 (0.040)
Adoption of Premium-grade SPF-PL in 2023 (1/0)	0.058 (0.162)	0.465 (0.339)
Constant	-0.309 (1.142)	0.586 (2.294)
Control group: Dependent variable mean	0.024	0.046
Control group: Dependent variable SD	(0.155)	(0.211)
Treatment 3 Mean (Free-PL non-recipient)	0.105	0.176
Treatment 3 SD (Free-PL non-recipient)	(0.308)	(0.383)
Treatment 4 Mean (Free-PL non-recipient)	0.082	0.151
Treatment 4 SD (Free-PL non-recipient)	(0.275)	(0.360)
Treatment 5 Mean (Free-PL non-recipient)	0.063	0.119
Treatment 5 SD (Free-PL non-recipient)	(0.244)	(0.326)
Observations	772	434
R-squared	0.137	0.276
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Taken together, these results are mildly suggestive of a behavioral barrier rooted in reference dependence, especially for Mid-grade SPF-PL. Farmers who previously received the technology for free may have anchored on the zero price, leading to reduced valuation and take-up even in the presence of substantial subsidies. This behavioral response is consistent with the idea that expectations formed through earlier subsidies can undermine the effectiveness of cost-sharing strategies in subsequent periods. The pattern of results is broadly consistent with the hypothesis that prior free receipt anchored farmers' price expectations, although the estimates are imprecise and should be interpreted with caution.

To further analyze the experience effect, we examine farmers' use of SPF-PL and its impact on yield and mortality in the pre-intervention years (2022 and 2023). We analyze this using a two-Way Fixed Effects (TWFE) model, and present the results in appendix I. The findings indicate that farmers who used mid-grade SPF-PL did not experience higher yields or lower mortality in 2022 and 2023, which helps explain their reluctance toward adopting mid-grade SPF-PL in 2024.

From a policy perspective, these findings might caution against the repeated use of fully subsidized programs without a clear transition path. While free provision may temporarily increase initial exposure, it risks anchoring farmers' price expectations, thereby reducing their willingness to pay in future rounds—even when the technology may prove to be beneficial.

(iii) Learning from risk and mortality experience

Table 10 presents estimates from regressions interacting treatment assignment with selfreported exposure to Cyclone Remal in May 2024. For Mid-grade SPF-PL, we find no statistically significant differences in adoption behavior at the extensive margin between cyclone-exposed and non-exposed farmers across treatment groups.

In contrast, for Premium-grade SPF-PL, the interaction effects suggest a significant negative association between recent exposure to the cyclone and adoption decisions (see Table 11. In treatment group 3 (highest discount recipients) farmers who experienced cyclone-related disruptions are 14.9 percentage points (full sample, at $p < 0.05$) and 23.7 percentage points (active farmers, at $p < 0.10$) less likely to adopt Premium-grade

SPF-PL compared to their non-exposed counterparts. Similarly, in treatment group 5 (lowest discount recipients), cyclone-affected farmers are 28.8 percentage points less likely to adopt ($p < 0.05$). While the remaining interaction terms are also negative, they are not statistically significant. These results are consistent with the hypothesis that recent exposure to a natural disaster imposes capital constraints that cannot be fully offset by moderate price discounts.

The findings underscore the importance of timing and context in shaping technology adoption behavior. For more expensive inputs like Premium-grade SPF-PL, price reductions alone may be insufficient when farmers are simultaneously recovering from shocks. This highlights the need for complementary interventions—such as targeted financial assistance or deferred payment schemes—for farmers facing acute liquidity constraints. More broadly, these results reinforce the role of lived experiences in shaping perceived vulnerability and willingness to adopt new technologies, suggesting that interventions following natural disasters may offer strategic leverage points for encouraging uptake.

We also examine whether prior experience with shrimp mortality influenced responsiveness to the voucher treatments by interacting treatment assignment with a binary indicator for reported mortality in 2023. Table 12 and Table 13 report the results for Mid-grade and Premium-grade SPF-PL, respectively. Across both cases, we do not find statistically significant differences in adoption behavior between treated farmers who experienced shrimp mortality and those who did not.

This finding is noteworthy given that a central motivation for promoting SPF-PL is its purported ability to reduce shrimp mortality. The absence of differential treatment effects suggests that this messaging alone may not have been sufficient to shift adoption behavior, even among farmers who had recently experienced production losses. It may reflect limited recall or salience of past losses, or competing constraints that outweigh prior negative experiences.

Table 10: Heterogeneous impact of discount vouchers by cyclone exposure on the adoption of Mid-grade SPF-PL

	Adoption of Mid-grade SPF-PL (1/0)	
Variables	(1) Full Sample	(2) Active Farmers
Treatment 1: BDT 100 off from BDT 800 type	0.015 (0.041)	0.015 (0.080)
Treatment 2: BDT 50 off from BDT 800 type	-0.005 (0.050)	-0.014 (0.096)
Cyclone-affected farm in May 2024 (1/0)	-0.041 (0.059)	-0.110 (0.149)
Treatment 1 × Cyclone-affected farm	0.038 (0.068)	0.175 (0.148)
Treatment 2 × Cyclone-affected farm	0.110 (0.082)	0.192 (0.191)
Farm flooded in Aug 2024 (1/0)	-0.056* (0.032)	-0.076 (0.067)
Distance to Khulna (in km)	0.002 (0.015)	-0.006 (0.057)
Adoption of Mid-grade SPF-PL in 2023 (1/0)	0.099 (0.085)	0.172 (0.183)
Constant	-0.157 (0.883)	0.277 (3.478)
Control group: Dependent variable mean	0.091	0.172
Control group: Dependent variable SD	(0.289)	(0.380)
Treatment 1 Mean (Cyclone-unaffected)	0.112	0.203
Treatment 1 SD (Cyclone-unaffected)	(0.316)	(0.404)
Treatment 2 Mean (Cyclone-unaffected)	0.084	0.151
Treatment 2 SD (Cyclone-unaffected)	(0.278)	(0.360)

Variables	Adoption of Mid-grade SPF-PL (1/0) (1) Full Sample	 (2) Active Farmers
Observations	561	299
R-squared	0.241	0.325
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 11: Heterogeneous impact of discount vouchers by cyclone exposure on the adoption of Premium-grade SPF-PL

Variables	Adoption of Premium-grade SPF-PL (1/0) (1) Full Sample	 (2) Active Farmers
Treatment 3: BDT 500 off from BDT 1200 type	0.141*** (0.032)	0.244*** (0.070)
Treatment 4: BDT 400 off from BDT 1200 type	0.091*** (0.033)	0.173** (0.071)
Treatment 5: BDT 200 off from BDT 1200 type	0.092** (0.035)	0.177*** (0.064)
Cyclone-affected farm in May 2024 (1/0)	0.070 (0.042)	0.160* (0.092)
Treatment 3 × Cyclone-affected farm	-0.149** (0.067)	-0.237* (0.140)
Treatment 4 × Cyclone-affected farm	-0.040 (0.063)	-0.130 (0.109)
Treatment 5 × Cyclone-affected farm	-0.097 (0.070)	-0.288** (0.139)
Farm flooded in Aug 2024 (1/0)	-0.001 (0.024)	-0.029 (0.040)
Distance to Khulna (in km)	0.006 (0.020)	-0.005 (0.040)
Adopted Premium-grade SPF-PL in 2023 (1/0)	0.060 (0.171)	0.546 (0.335)
Constant	-0.407 (1.137)	0.183 (2.306)
Control group: Dependent variable mean	0.024	0.046
Control group: Dependent variable SD	(0.155)	(0.211)

Variables	Adoption of Premium-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment 1 Mean (Cyclone-unaffected)	0.122	0.200
Treatment 1 SD (Cyclone-unaffected)	(0.328)	(0.402)
Treatment 2 Mean (Cyclone-unaffected)	0.081	0.151
Treatment 2 SD (Cyclone-unaffected)	(0.275)	(0.360)
Treatment 3 Mean (Cyclone-unaffected)	0.081	0.145
Treatment 3 SD (Cyclone-unaffected)	(0.275)	(0.354)
Observations	772	434
R-squared	0.143	0.286
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 12: Heterogeneous impact of discount vouchers by prior shrimp mortality experience on Adoption of Mid-grade SPF-PL

Variables	Adoption of Mid-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment 1 (BDT 100 off from BDT 800 type)	-0.021 (0.048)	0.033 (0.150)
Treatment 2 (BDT 50 off from BDT 800 type)	-0.036 (0.063)	-0.081 (0.153)
Faced shrimp mortality in 2023 (1/0)	-0.013 (0.072)	0.011 (0.132)
Treatment Group 1 × Faced shrimp mortality	0.076 (0.069)	0.047 (0.186)
Treatment Group 2 × Faced shrimp mortality	0.103 (0.085)	0.175 (0.181)
Farm flooded in Aug 2024 (1/0)	-0.059* (0.033)	-0.081 (0.065)
Distance to Khulna (in km)	0.000 (0.015)	-0.016 (0.056)
Adopted Mid-grade SPF-PL in 2023 (1/0)	0.085 (0.088)	0.153 (0.177)
Constant	-0.047	0.841

Variables	Adoption of Mid-grade SPF-PL (1/0) (1) Full Sample	(2) Active Farmers
	(0.907)	(3.410)
Control group: Dependent variable mean	0.091	0.172
Control group: Dependent variable SD	(0.289)	(0.380)
Treatment 1 Mean (No Mortality)	0.097	0.269
Treatment 1 SD (No Mortality)	(0.298)	(0.452)
Treatment 2 Mean (No Mortality)	0.068	0.139
Treatment 2 SD (No Mortality)	(0.253)	(0.351)
Observations	561	299
R-squared	0.244	0.329
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 13: Heterogeneous impact of discount vouchers by prior shrimp mortality experience on Adoption of Premium-grade SPF-PL

Variables	Adoption of Premium-grade SPF-PL (1/0) (1) Full Sample	(2) Active Farmers
Treatment 3 (BDT 500 off from BDT 1200 type)	0.107** (0.043)	0.224** (0.095)
Treatment 4 (BDT 400 off from BDT 1200 type)	0.053 (0.041)	0.116 (0.120)
Treatment 5 (BDT 200 off from BDT 1200 type)	0.030 (0.047)	0.079 (0.128)
Faced shrimp mortality in 2023 (1/0)	-0.053* (0.031)	-0.047 (0.082)
Treatment 3 × Faced shrimp mortality	-0.011 (0.051)	-0.055 (0.103)
Treatment 4 × Faced shrimp mortality	0.043 (0.051)	0.038 (0.118)
Treatment 5 × Faced shrimp mortality	0.052 (0.060)	0.029 (0.145)
Distance to Khulna (in km)	0.004 (0.020)	-0.014 (0.041)

Variables	Adoption of Premium-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Farm flooded in 2023 (1/0)	0.037 (0.039)	0.050 (0.068)
Adopted Premium-grade SPF-PL in 2023 (1/0)	0.048 (0.162)	0.440 (0.330)
Constant	-0.237 (1.144)	0.785 (2.305)
Control group: Dependent variable mean	0.024	0.046
Control group: Dependent variable SD	(0.155)	(0.211)
Treatment 1 Mean (No Mortality)	0.200	0.239
Treatment 1 SD (No Mortality)	(0.402)	(0.431)
Treatment 2 Mean (No Mortality)	0.081	0.226
Treatment 2 SD (No Mortality)	(0.275)	(0.425)
Treatment 3 Mean (No Mortality)	0.081	0.185
Treatment 3 SD (No Mortality)	(0.275)	(0.396)
Observations	772	434
R-squared	0.139	0.277
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

(iv) Value of infrastructure preparedness: by having a nursing facility

We examine whether prior use of nursing facilities at baseline (2023) moderated farmers' responsiveness to discount vouchers for SPF-PL. The rationale behind this heterogeneity analysis is that farmers who adopted nursing practices in the past may have higher baseline awareness of shrimp health risks or greater technical capacity to handle vulnerable PL, potentially shaping both their preferences and perceived benefits of SPF-PL. In both the regressions for Mid-grade and Premium-grade SPF-PL, we include interaction terms between voucher treatments and a binary indicator for prior use of nursing facilities.

In the case of Mid-grade SPF-PL (Table 14), the interaction between Treatment Group 2 (BDT 50 off from BDT 800) and prior nursing facility use is statistically significant and positive in the full sample ($\beta = 0.146$, $p < 0.1$). This suggests that farmers who previously used nursing facilities were significantly more likely to adopt SPF-PL in response to even a modest discount. The magnitude of the interaction for active farmers ($\beta = 0.146$) is larger but not statistically significant at conventional levels, likely due to lower power in the subsample. Meanwhile, interaction terms for Treatment Group 1 (BDT 100 off) are small and statistically insignificant across both samples. The main effect of having used a nursing facility is negative but imprecise, indicating that prior nursing alone does not predict higher adoption in the absence of a discount.

In the Premium-grade SPF-PL results (Table 15), the interaction terms for Treatment Groups 4 and 5 (BDT 400 and BDT 200 discounts from the BDT 1200 price point, respectively) are positive and statistically significant in the full sample. Farmers with prior nursing experience who received these smaller discounts were 10–11 percentage points more likely to adopt compared to non-nursing farmers in the same treatment arms. The interaction with the largest discount (Treatment Group 3, BDT 500 off) is not significant, suggesting a possible ceiling effect in responsiveness. In the active farmer subsample, the interaction coefficients are similarly positive but imprecisely estimated. Taken together, these results suggest that past nursing behavior serves as a marker for receptivity to health-oriented technologies like SPF-PL, particularly when incentives are modest.

Table 14: Heterogeneous impact of discount vouchers by prior nursing facility use on Adoption of Mid-grade SPF-PL

	Adoption of Mid-grade SPF-PL (1/0)	
Variables	**(1) Full Sample**	**(2) Active Farmers**
Treatment Group 1 (BDT 100 off from BDT 800 type)	0.029 (0.043)	0.059 (0.077)
Treatment Group 2 (BDT 50 off from BDT 800 type)	-0.027 (0.057)	-0.039 (0.114)
Used nursing facility in baseline (1/0)	-0.062 (0.055)	-0.070 (0.111)
Treatment Group 1 × Used nursing facility	0.003 (0.074)	0.024 (0.143)
Treatment Group 2 × Used nursing facility	0.146* (0.083)	0.198 (0.162)
Farm flooded in Aug 2024 (1/0)	-0.055 (0.033)	-0.069 (0.070)
Distance to Khulna (in km)	0.001 (0.015)	-0.012 (0.059)
Adopted Mid-grade SPF-PL in 2023 (1/0)	0.104 (0.085)	0.182 (0.175)
Constant	-0.062 (0.875)	0.624 (3.551)
Control group: Dependent variable mean	0.091	0.172
Control group: Dependent variable SD	(0.289)	(0.380)
Treatment 1 Mean (No Nursing)	0.111	0.203
Treatment 1 SD (No Nursing)	(0.316)	(0.405)
Treatment 2 Mean (No Nursing)	0.080	0.161
Treatment 2 SD (No Nursing)	(0.272)	(0.371)
Observations	561	299

Variables	Adoption of Mid-grade SPF-PL (1/0) (1) Full Sample	(2) Active Farmers
R-squared	0.247	0.327
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

Table 15: Heterogeneous impact of discount vouchers by prior nursing facility use on Adoption of Premium-grade SPF-PL

	Adoption of Premium-grade SPF-PL (1/0)	
Variables	(1) Full Sample	(2) Active Farmers
Treatment Group 3 (BDT 500 off from BDT 1200 type)	0.100*** (0.030)	0.200*** (0.061)
Treatment Group 4 (BDT 400 off from BDT 1200 type)	0.037 (0.028)	0.099 (0.068)
Treatment Group 5 (BDT 200 off from BDT 1200 type)	0.028 (0.031)	0.061 (0.063)
Used nursing facility in baseline (1/0)	-0.046* (0.027)	-0.042 (0.064)
Treatment Group 3 × Used nursing facility	0.005 (0.048)	-0.028 (0.083)
Treatment Group 4 × Used nursing facility	0.115** (0.051)	0.109 (0.094)
Treatment Group 5 × Used nursing facility	0.102* (0.051)	0.113 (0.106)
Farm flooded in Aug 2024 (1/0)	0.001 (0.023)	-0.023 (0.040)
Distance to Khulna (in km)	0.005 (0.020)	-0.010 (0.040)
Adopted Premium-grade SPF-PL in 2023 (1/0)	0.055 (0.163)	0.423 (0.368)
Constant	-0.352 (1.136)	0.549 (2.306)
Control group: Dependent variable mean	0.024	0.046
Control group: Dependent variable SD	(0.155)	(0.211)
Treatment Group 3 Mean (No Nursing)	0.0488	0.088

Variables	Adoption of Premium-grade SPF-PL (1/0)	
	(1) Full Sample	(2) Active Farmers
Treatment Group 3 SD (No Nursing)	(0.216)	(0.286)
Treatment Group 4 Mean (No Nursing)	0.064	0.123
Treatment Group 4 SD (No Nursing)	(0.246)	(0.331)
Treatment Group 5 Mean (No Nursing)	0.130	0.234
Treatment Group 5 SD (No Nursing)	(0.338)	(0.426)
Observations	772	434
R-squared	0.143	0.279
Cluster Fixed Effects	Yes	Yes
Sample-type Fixed Effects	Yes	Yes
LASSO-picked controls	Yes	Yes

Source: Authors' calculations.

Note: Standard errors are clustered at the cluster level. *** p<0.01, ** p<0.05, * p<0.1. LASSO-picked controls include farmer age, years of education, owned pond area, history of pond flooding in 2023, local availability of SPF-PL before the intervention, pre-intervention intention to stock Bagda, receipt of free PL in 2023, and whether the pond was deepened in 2023.

8 LIMITATIONS

Our study is not without limitations. First, one might wonder if our analysis of Midgrade SPF-PL may be constrained by statistical power. However, as shown in Appendix Section C, baseline adoption rates were inflated due to the free distribution of SPF-PL in the prior year. When excluding those who received it for free, the adjusted adoption rate was approximately 7.5%, which closely aligns with the endline adoption rate. Given our sample size, this allowed us to detect treatment effects of roughly 10–12 percentage points. However, the study may be underpowered to detect smaller yet potentially policy-relevant effects below this threshold.

Second, the analysis among active farmers is further constrained by sample size, which may limit power to detect modest effects. Moreover, we measure adoption over a single post-intervention season, which does not capture long-term behavioral shifts or learning dynamics. Although Black-tiger shrimp farming is not seasonally fixed, environmental shocks such as flooding or cyclones can disrupt salinity and infrastructure, potentially affecting outcomes. The intervention window was further limited by logistical constraints—specifically, an early start would have allowed greater coverage of active farmers, and a later voucher expiration could have accommodated delayed adoption. However, our study timeline, including endline data collection, was bounded by funding requirements that necessitated completion of activities by December 2024.

Third, while we took measures to limit direct spillovers—such as verifying voucher eligibility via national ID (NID) numbers—it is not fully impossible that indirect sharing of SPF-PL occurred after purchase. However, we verified reported adoption by tracking purchases from Desh Bangla (the official distributor) for farmers including the ones in the control group. Our records indicate that control farmers who purchased SPF-PL did so directly from Desh Bangla rather than through peer farmers. Moreover, the average price they paid for SPF-PL was equal to the full market price, suggesting that the likelihood of post-purchase sharing was very low.

Fourth, due to staggered harvest schedules, we only could collect self-reported expectations for yield and mortality in the endline for many of the farmers who cultivated Black-tiger shrimp, not realized outcomes. Future work could revisit these farms to verify whether the technology translated into actual productivity gains.

Finally, the study was conducted in a specific geography (Khulna, Bagerhat, Satkhira) and under a particular institutional setup (Desh Bangla as the sole distributor). While this region was the largest hub for shrimp farmers in Bangladesh, caution should be exercised in generalizing findings to other regions with different market structures or institutional supports.

Despite these constraints, the study provides valuable evidence on adoption behavior under price, availability and information frictions.

9 DISCUSSIONS AND CONCLUSION

This study evaluates the impact of price discounts on the adoption of Specific Pathogen Free post-larvae (SPF-PL) among shrimp farmers in southwestern Bangladesh, a region facing high output losses due to disease-driven shrimp mortality. We randomly assigned farmers to receive vouchers that reduced the prices of two types of SPF-PL—Mid-grade and Premium-grade—to match or undercut the price of the widely used, but more diseaseprone, normal hatchery PL. Importantly, the intervention occurred in a competitive input landscape where normal PL is not only more familiar and widely available, but also commonly sold on credit—unlike SPF-PL, which must be purchased in cash.

Our findings reveal that price discounts alone were insufficient to shift adoption for Midgrade SPF-PL. By contrast, we find statistically significant positive effects of the vouchers on Premium-grade SPF-PL adoption, especially among farmers who actively cultivated shrimp during the study period. These results highlight the importance of perceived input quality: adoption rates increased by 6 to 10 percentage points in the full sample and by

10 to 19 percentage points among active shrimp farmers. However, coefficient equality tests indicate that the effects of larger discounts are not statistically different from those of smaller discounts. In other words, lowering the price of Premium-grade SPF-PL to fully match that of normal hatchery PL does not generate a significantly higher adoption rate than offering a smaller discount—one that reduces only less than half of the price gap.

We also document meaningful heterogeneity in adoption responses. Farmers who had prior exposure to Mid-grade SPF-PL—through free receipt or participation in the 2023 multi-actor intervention—were less likely to adopt the same product again, suggesting the presence of experience effects and reference dependence. Interestingly, prior exposure to Mid-grade SPF-PL appears to have encouraged switching to the higher-quality Premiumgrade SPF-PL variant, reinforcing the idea that farmer learning influences input choices over time.

Contextual constraints also shaped adoption. Farmers exposed to a recent natural disaster (cyclone Remal in May 2024) were significantly less likely to adopt Premium-grade SPF-PL, even with the price discount, suggesting that capital constraints induced by shocks can undermine technology adoption.

Moreover, treated farmers who had infrastructure preparedness—such as installing a nursing facility—were more likely to adopt than the ones who did not install one, indicating that complementary infrastructure preparedness play a critical role in technology uptake. Overall, our findings contribute to the mixed literature on input subsidies and technology adoption by documenting both a lack of responsiveness to a discounted product that, despite being advertised as good quality, was perceived by farmers as inadequate to re-adopt, and a positive adoption response to an alternative discounted product perceived as higher quality.

A key insight from this study is that farmers can be effectively nudged toward adopting higher-quality agricultural inputs when the quality differential is clearly perceived or credibly signaled. Beyond the context of shrimp farming, these findings offer broader insights for technology promotion in aquaculture and agriculture. With their experience of adopting Premium-grade SPF-PL, it may be worth exploring how the medium and long-term learning and adoption behavior get adjusted. Farmer experience and exposure history should inform targeting strategies. Interventions may yield higher returns when directed toward infrastructurally aware and prepared farmers—particularly when paired with price incentives and simple information. At the same time, a uniform approach is unlikely to succeed. Farmers who experienced shock in terms of capital investments may require more tailored engagement, such as personalized advisory services or credits.

Together, these findings offer several implications for agricultural technology promotion in low-income contexts:

- **Farmers value quality if affordability improves:** Even in the presence of cheaper, familiar alternatives, a sizable share of farmers opted for higher-quality inputs when affordability improved. From a policy perspective, our finding implies that even smaller (BDT 200= $2 per thousand PL), well-targeted discounts could be effective in promoting the adoption of quality inputs.
- **Behavioral perceptions matter:** Past exposure to a technology—whether successful or not—can strongly shape future adoption behavior through reference dependence or learning.
- **Targeting matters:** Interventions may yield higher returns when directed at infrastructurally prepared farmers and those less affected by recent shocks.
- **Support may need to be multifaceted:** Financial incentives alone may be insufficient in shock-prone areas where natural disasters regularly disrupt livelihoods. Bundling price discounts with complementary interventions—such as liquidity support or post-disaster recovery mechanisms—may help overcome adoption barriers. While this study does not test such bundled approaches, future research could explore their effectiveness.

Looking forward, future research should examine the persistence of adoption beyond a single season and assess realized (not just expected) productivity gains. Understanding how farmers' experiences evolve—and how adoption behavior adjusts in response to longterm risk perceptions, liquidity constraints, and input markets—remains a critical area for advancing sustainable and inclusive aquaculture development.

REFERENCES

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. M. (2022). When should you adjust standard errors for clustering? The Quarterly Journal of Economics, 138(1):1– 35.

Aggarwal, S., Giera, B., Jeong, D., Robinson, J., and Spearot, A. (2024). Market access, trade costs, and technology adoption: Evidence from northern Tanzania. The Review of Economics and Statistics, 106(6):1511–1528.

Ahmed, N. and Troell, M. (2010). Fishing for prawn larvae in Bangladesh: an important coastal livelihood causing negative effects on the environment. Ambio, 39(1):20–29.

Ahmed, S., McIntosh, C., and Sarris, A. (2020). The impact of commercial rainfall index insurance: Experimental evidence from Ethiopia. American Journal of Agricultural Economics, 102(4):1154–1176.

Ali, H., Haque, M. M., and Murshed-e Jahan, K. (2025). Transformation of the farm segment of the aquaculture value chain in southern Bangladesh. Aquaculture, 596(Part 1):741730.

Anderson, J. L., Asche, F., Garlock, T., and Chu, J. (2017). Aquaculture: Its role in the future of food. In World Agricultural Resources and Food Security, volume 17, pages 159–173. Emerald Group Publishing Limited.

Aqua Culture Asia Pacific (2024). Marine shrimp in Asia: Production mired by low prices and disease outbreaks in 2022. Accessed 21 October 2025.

Beaman, L., Ben Yishay, A., Magruder, J., and Mobarak, A. M. (2013). Can network theory-based targeting increase technology adoption? American Economic Review, 103(3):386–392.

Belloni, A., Chernozhukov, V., and Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. The Review of Economic Studies, 81(2):608–650.

Belton, B., Karim, M., Thilsted, S. H., Jahan, K. M., Collis, W., and Phillips, M. (2011). Review of aquaculture and fish consumption in Bangladesh. Technical Report 2011-58, WorldFish Center, Penang, Malaysia.

Bush, S. R., Belton, B., Hall, D., Vandergeest, P., Murray, F. J., Ponte, S., and Kusumawati, R. (2013). Certify sustainable aquaculture? Science, 341(6150):1067– 1068.

Cai, J., de Janvry, A., and Sadoulet, E. (2020). Subsidy policies and insurance demand. American Economic Review, 110(8):2422–2453.

Carter, M., Laajaj, R., and Yang, D. (2021). Subsidies and the African green revolution: Direct effects and social network spillovers of randomized input subsidies in Mozambique. American Economic Journal: Applied Economics, 13(2):206–229.

Carter, M. R. and Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. Journal of Development Studies, 42(2):178–199.

Cohen, J. and Dupas, P. (2010). Free distribution or cost-sharing? evidence from a randomized malaria prevention experiment. Quarterly Journal of Economics, 125(1):1– 45.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., and Vickery, J. (2013). Barriers to household risk management: Evidence from India. American Economic Journal: Applied Economics, 5(1):104–135.

Cole, S. A. and Fernando, A. N. (2020). 'Mobile'ising agricultural advice: Technology adoption, diffusion and sustainability. The Economic Journal, 131(633):192–219.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. American Economic Review, 100(1):35–69.

Dar, M., Suri, T., and Emerick, K. (2024). Private input suppliers as information agents for technology adoption in agriculture. American Economic Journal: Applied Economics.

Dasgupta, S., Laplante, B., Meisner, C., Wheeler, D., and Yan, J. (2008). The impact of sea level rise on developing countries: A comparative analysis. Climatic Change, 93(3-4):379–388.

Dercon, S. and Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. Journal of Development Economics, 96(2):159– 173.

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. American Economic Review, 101(6):2350–2390.

Dupas, P. (2014). Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. Econometrica, 82(1):197–228.

FAO (2022). The State of World Fisheries and Aquaculture 2022: Towards Blue Transformation. Food and Agriculture Organization of the United Nations, Rome.

Fischer, G., Karlan, D., McConnell, M., and Raffler, P. (2019). Targeting technology to increase adoption and reduce inequity: Evidence from a randomized field experiment in Uganda. Journal of Development Economics, 142:102–111.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. Journal of Political Economy, 103(6):1176–1209.

Gignoux, J., Mespl´e-Somps, S., and Zongo, T. (2023). Subsidized inputs and agricultural productivity: Experimental evidence from Haiti. American Journal of Agricultural Economics, 105(1):3–24.

Haque, I. (2025). The role of land market in achieving the scale for adaptation to climate change: Evidence from Bangladesh. Accessed via Dropbox.

Islam, M. M., Sallu, S., Hubacek, K., and Paavola, J. (2014). Limits and barriers to adaptation to climate variability and change in Bangladeshi coastal fishing communities. Marine Policy, 43:208–216.

Islam, M. S. (2008). From pond to plate: Towards a twin-driven commodity chain in Bangladesh shrimp aquaculture. Food Policy, 33(3):209–223.

Jayne, T. S., Mason, N. M., Burke, W. J., and Ariga, J. (2018). Taking stock of Africa's second-generation agricultural input subsidy programs. Food Policy, 75:1–14.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2):263–291.

Karim, M., Sarwer, R. H., Brooks, A. C., Gregory, R., Jahan, M. E., and Belton, B. (2011). The incidence of suspected white spot syndrome virus in semi-intensive and extensive shrimp farms in Bangladesh: implications for management. Aquaculture Research, 43(3):421–430.

Kerwin, J. T. (2025). Scared straight or scared to death? fatalism in response to disease risks. The Economic Journal, 135(670):1923–1941.

Kerwin, J. T., Rostom, N., and Sterck, O. (2024). Striking the right balance: Why standard balance tests over-reject the null, and how to fix it. IZA Discussion Paper 17217, IZA – Institute of Labor Economics.

Kremer, M. and Miguel, E. (2007). Worms: Identifying impacts on education and health in the presence of treatment externalities. Econometrica, 72(1):159–217.

Köszegi, B. and Rabin, M. (2006). A model of reference-dependent preferences. The Quarterly Journal of Economics, 121(4):1133–1165.

Little, D. C., Newton, R. W., and Beveridge, M. C. M. (2016). Aquaculture: a rapidly growing and significant source of sustainable food? status, transitions and future. Proceedings of the Nutrition Society, 75(3):274–286.

Liverpool-Tasie, L. S. O., Dillon, A., Bloem, J. R., and Adjognon, G. S. (2025). Private sector promotion of agricultural technologies: Experimental evidence from Nigeria. Journal of Environmental Economics and Management, 133:103201.

Maredia, M. K., Farris, J., Mason, N. M., and Morgan, S. (2025). Does providing free trial packs with demonstration plots increase the adoption of agricultural technologies? cost effectiveness evidence from Tanzania. Agricultural Economics.

Michelson, H., Fairbairn, A., Ellison, B., Maertens, A., and Manyong, V. (2021). Misperceived quality: Fertilizer in Tanzania. Journal of Development Economics, 148:102579.

Mobarak, A. M., Dwivedi, P., Bailis, R., Hildemann, L., and Miller, G. (2012). Low demand for nontraditional cookstove technologies. Proceedings of the National Academy of Sciences, 109(27):10815–10820.

Narayanan, S., Belton, B., Kabir, R., Sakil, A. Z., Khan, A. H., and Hernandez, R. (2025). The cluster panacea? An Evaluation of Three Interventions in Shrimp Value

Chains in Bangladesh. CGIAR initiative on rethinking food markets technical report, International Food Policy Research Institute (IFPRI), Washington, DC.

Savary, S., Willocquet, L., et al. (2019). The global burden of pathogens and pests on major food crops. Proceedings of the National Academy of Sciences, 116(12):4843– 4848.

Subasinghe, R., Soto, D., and Jia, J. (2009). Global aquaculture and its role in sustainable development. Reviews in Aquaculture, 1(1):2–9.

The Business Standard (2023). Shrimp exports sink as western consumers tighten spending. Accessed June 2, 2025.

Washim, M. R., Rahman, S. L., and Nahar, S. (2016). Culture potential of spf (specific pathogen-free) shrimp (penaeus monodon) with special context of its growth and production performance in south-west coastal region of bangladesh. International Journal of Fisheries and Aquatic Studies, 4(6):339–344.

World Bank (2024). Climate risk country profile: Bangladesh. https://climateknowledgeportal.worldbank.org/sites/default/files/country-profiles/16813-WB_Bangladesh%20Country%20Profile-WEB.pdf. Accessed: 2025-07-14.

APPENDIX

A Sampling strategy for multi-actor intervention program evaluation in 2023

To evaluate the 2023 multi-actor intervention programs implemented by the Department of Fisheries (DoF), ACI Agrolink Ltd. (ACI), and the Bangladesh Shrimp and Fish Foundation (BSFF), IFPRI sampled farmers from 60 designated village clusters. The sample included three groups: (i) program participants, (ii) non-participants from the same village, and (iii) non-participants from nearby villages. The sampling strategy and criteria for selecting clusters and farmer groups are described below.

2023 intervention program-participant farmers formed groups based on guidelines set by DoF, ACI, or BSFF, and engaged in coordinated production across contiguous ponds. DoF program participants were sampled using a two-stage random sampling strategy: 60 clusters were randomly drawn from a registry of 300 clusters maintained by the Sustainable Coastal and Marine Fisheries Project (SCMFP), followed by 7 farmers per cluster.

Dropouts were retained in the sample, with replacements added as needed, yielding 444 DoF progam participant farmers. In contrast, a census of all farmers in eight functional clusters managed by BSFF (4 clusters, 20 farmers per cluster, with a total of 80 farmers) and ACI (4 clusters, 25 farmers per cluster with a total of 98 farmers) was conducted, adjusting for two ineligible cases.

Non-participants were selected via random sampling from a census of shrimp farmers in the same or adjacent villages. For DoF clusters, 3 non-participants from the same village and 4 from an adjacent village per cluster were sampled. For BSFF, the corresponding numbers were 8 and 12; for ACI, 12 and 13.

B Vouchers and logistics

Figure B1: Coupons and Pamphlet Display: English version

(a) Treatment 1

(b) Treatment 2

(c) Treatment 3

(d) Treatment 4

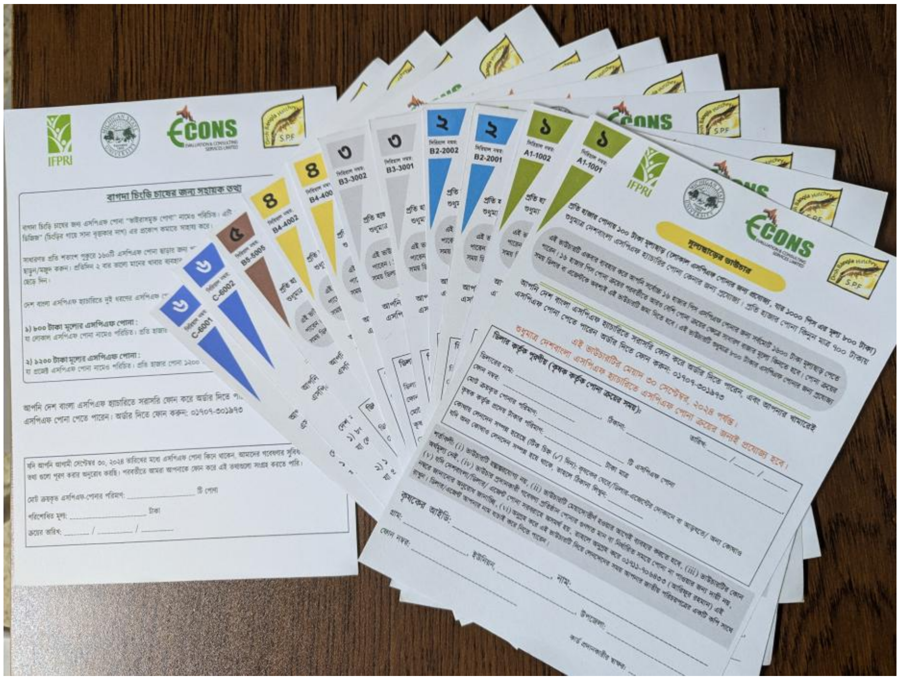
(e) Treatment 5

(f) Control Group

(g) Information Pamphlet
(All Groups)

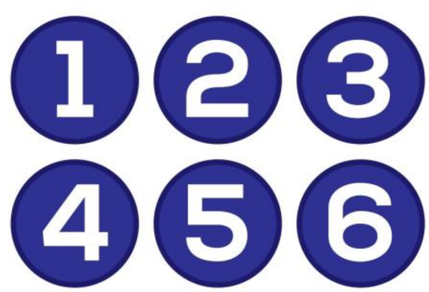
Source: Authors.

Figure B2: Visual Materials Used in the Intervention



(a) Discount vouchers: printed translated version

(b) Opaque jute bag used to conduct the lottery.



(c) Number tokens (made of plastic) corresponding to the voucher types.

Source: Authors.

C Power calculation

We designed the study with a fixed sample of 1,222 shrimp farmers, randomized at the individual level across six experimental arms: one control group, two treatment arms targeting Mid-grade SPF post-larvae (PL), and three treatment arms targeting Premium-grade SPF-PL.

Our primary outcome of interest is the binary adoption of SPF-PL in the 2024 season. Here, we present an ex-ante power calculations by type of SPF-PL to calculate the minimum detectable effects (MDE), using 2023 administrative and survey data as a baseline. We focused power calculations on adoption (1/0) of SPF-PL by type, given its centrality to the research question and policy relevance. Secondary outcomes, such as mortality and yield, are not used to power the study. Our randomization was based on an individuallevel public lottery. Hence, we did not have a prior idea on how the distribution among the treatment groups may turn out.

For Mid-grade SPF-PL, the observed baseline adoption rate in the control group was 26%. However, this figure likely overstates the true baseline adoption rate in a context without external support. Notably, 20.4% of farmers in our sample received Mid-grade SPF-PL for free through a multi-actor intervention program conducted in the previous year. When we exclude these free recipients, only 6.5% of farmers (n = 930) adopted Mid-grade SPF-PL, providing a more conservative and policy-relevant estimate of the baseline.

Using this 6.5% figure as the control group mean, we conducted power calculations under various sample size scenarios to determine the minimum detectable effect (MDE) at 80% power and a 5% significance level (two-sided test). As shown in Panel A of Table C1, the MDE under a conservative scenario with 160 farmers in both treatment and control groups is approximately 10 percentage points. In a more favorable scenario with 200 in each group, the MDE falls to 8.7 percentage points.

For Premium-grade SPF-PL, the baseline adoption rate was extremely low (0.8%), making direct use of the observed mean impractical for power analysis. We therefore conservatively assumed a control group mean of 2%, reflecting a plausible adoption rate in the absence of any discounts. Given the larger price differential—BDT 500—between conventional PL (BDT 700 per 1,000) and Premium-grade SPF-PL (BDT 1,200 per 1,000), an additional high-discount treatment arm was included. As shown in Panel B of Table C1, the MDE under realistic scenarios ranges from 7.2 percentage points (for N = 160 in both groups) to 6.0 percentage points (for N = 200 in both groups).

Table C1: Minimum Detectable Effects (MDE) for Adoption of SPF-PL by Type and Sample Size Scenario

Panel A: Mid-grade SPF-PL (Sample mean adoption rate = 6.5%)						
Treat N	**Control N**	**Total N**	**Control (sample) Mean**	**Treatment Mean**	**MDE**	**MDE (% of Baseline)**
160	160	320	0.065	0.165	0.100	153.1%
160	170	330	0.065	0.163	0.098	150.6%
160	180	340	0.065	0.162	0.097	148.5%
160	190	350	0.065	0.160	0.095	146.6%
170	190	360	0.065	0.158	0.093	143.4%

Panel A: Mid-grade SPF-PL (Sample mean adoption rate = 6.5%)						
Treat N	**Control N**	**Total N**	**Control (sample) Mean**	**Treatment Mean**	**MDE**	**MDE (% of Baseline)**
180	180	360	0.065	0.158	0.093	142.3%
200	200	400	0.065	0.152	0.087	133.4%
200	220	420	0.065	0.150	0.085	130.5%
Panel B: Premium-grade SPF-PL (Assumed sample mean adoption rate = 2.0%)						
Treat N	**Control N**	**Total N**	**Control (sample) Mean**	**Treatment Mean**	**MDE**	**MDE (% of Baseline)**
160	160	320	0.020	0.092	0.072	358.0%
160	170	330	0.020	0.091	0.071	352.5%
160	180	340	0.020	0.090	0.070	347.5%
160	190	350	0.020	0.089	0.069	342.5%
170	190	360	0.020	0.087	0.067	333.5%
170	200	370	0.020	0.086	0.066	329.0%
180	200	380	0.020	0.084	0.064	320.5%
180	180	360	0.020	0.086	0.066	329.5%
200	200	400	0.020	0.081	0.061	306.0%
200	220	420	0.020	0.080	0.060	298.5%

Source: Authors' calculations.

Note: For Mid-grade SPF-PL, the control group mean is based on the baseline adoption rate excluding farmers who received Mid-grade SPF-PL for free. For Premium-grade, the observed baseline adoption rate was very low (0.8%); we use a slightly higher assumed rate (2%) to enable meaningful power calculations. Each row reports the minimum detectable effect (MDE) required to identify a statistically significant difference in adoption rates under a two-sided test with 5% significance and 80% power. The final column expresses the MDE as a percentage of the baseline adoption rate.

D Attrition and treatment assignment

Table D1: Effect of Treatment Group on Attrition

	Attrition (1/0)
Treatment 1: 100 taka off from BDT 800 type	-0.008 (0.015)
Treatment 2: 50 taka off from BDT 800 type	0.003 (0.015)
Treatment 3: 500 taka off from BDT 1200 type	0.009 (0.015)
Treatment 4: 400 taka off from BDT 1200 type	0.011 (0.015)
Treatment 5: 200 taka off from BDT 1200 type	0.008 (0.015)
Constant	0.018 (0.011)
Observations	1,195
R-squared	0.002

Source: Authors' calculations.

Note: This table reports OLS estimates of the impact of treatment assignment on survey attrition. Standard errors in parentheses. The control group is the omitted category.

E Motivation behind the intervention

Table E1: Association between farmers' perception of SPF-PL as expensive and their reported use of SPF-PL during the 2023 stocking season

Variables	Used SPF-PL in 2023 (1/0)
The farmer thought SPF-PL is too expensive before intervention	0.300*** (0.030)
Constant	0.324*** (0.014)
Observations	1,169
R-squared	0.077

Source: Authors' calculations.

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

F Black-tiger shrimp farming decision and treatment

We use the same regression setup as equation 2 and 3. We define decision to farm Black-tiger Shrimp in the year 2024 as the outcome variable for farmer i. The term $Y_i^{baseline}$ is a binary variable that indicates whether the farmer farmed Black Tiger Shrimp in 2023. The vector X_i includes variables selected via LASSO for this particular equation. Other variables are defined as before.

Table F1: Association between discount treatments and the decision to farm Black Tiger Shrimp

Variables	(1) Farmed Black-tiger shrimp in 2024 = 1
Treatment groups	
T1: 100 taka off from 800 taka type	-0.016 (0.052)
T2: 50 taka off from 800 taka type	0.025 (0.053)
T3: 500 taka off from 1200 taka type	0.061 (0.051)
T4: 400 taka off from 1200 taka type	0.017 (0.053)
T5: 200 taka off from 1200 taka type	0.040 (0.053)
Constant	0.530 (0.039)
Observations	1,169
R-squared	0.003

Source: Authors' calculations.

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

G Black-tiger shrimp farming decision and 2024 flood

Table G1: Association between Decision to Farm Bagda and 2024 Flood (considering the farms that did not farm before Aug 21, 2024)

Variables	(1) Farmed Black-tiger shrimp in 2024 = 1
Shrimp farm was affected by the flood in August 2024	-0.090*** (0.030)
The farmer is female	-0.130*** (0.037)
Years of schooling attended by the farmer	0.003 (0.003)
The sample pond is owned	0.009 (0.026)
Grew Bagda shrimp in 2023	0.082*** (0.028)
Constant	0.063* (0.038)
Observations	598
R-squared	0.030

Source: Authors' calculations.

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

H Benjamini-Hochberg (BH) False Discovery Rate

Table H1: Benjamini–Hochberg Adjusted P-values for Multiple Hypothesis Tests

Test ID	Raw p-value	BH-adjusted p-value	Significant at 5% FDR?
1	0.000	0.000	Yes
2	0.000	0.000	Yes
3	0.006	0.024	Yes
4	0.006	0.024	Yes
5	0.011	0.0264	Yes
6	0.012	0.0264	Yes
7	0.592	1.015	No
8	0.734	1.101	No
9	0.765	1.101	No
10	0.830	1.101	No
11	0.919	1.101	No
12	0.945	1.101	No

I Two-Way Fixed Effects Estimates for 2022-2023

To examine whether the use of mid-grade SPF-PL conferred measurable productivity benefits in the years prior to the 2024 voucher experiment, we estimate the following two-way fixed effects (TWFE) regression model:

$$Y_{it} = \alpha + \beta \cdot SPFPL_{it} + \boldsymbol{X'}_{it}\boldsymbol{\gamma} + \zeta_i + \delta_t + \theta_s + \varepsilon_{it},$$

where Y_{it} denotes the outcome of interest for farmer i in year t (mortality as a binary indicator, mortality rate in percent, or Bagda yield in kilograms). The key regressor, $SPFPL_{it}$, is an indicator for whether the farmer stocked mid-grade SPF-PL in that year. The vector $\boldsymbol{X}_{it}$ includes time-varying controls such as aquaculture land size, gender, age, years of schooling, flood exposure, and sample type (cluster, adjacent, or same-village farmer). Farmer fixed effects (ζ_i) account for time-invariant farmer characteristics, year fixed effects (δ_t) capture aggregate temporal shocks, and robust standard errors are clustered at the block level.

Results presented in Table I1 show no statistically significant effect of mid-grade SPF-PL use on any of the three outcomes in 2022–2023. The point estimates are small and imprecisely estimated: 0.021 for the mortality indicator, 2.576 for mortality rate, and 8.785 for yield, all with large standard errors. These results suggest that, prior to the 2024 discount voucher experiment, mid-grade SPF-PL adoption did not yield detectable improvements in survival or productivity relative to conventional post-larvae. This absence of measurable benefits provides important context for understanding farmer skepticism and resistance to mid-grade SPF-PL in subsequent interventions.

Table I1: Effect of SPF-PL Use on Mortality and Yield, 2022–2023 (TWFE Estimates)

	(1) Mortality (1/0)	(2) Mortality (%)	(3) Yield (kg)
SPF-PL Use	0.021 (0.036)	2.576 (3.003)	8.785 (8.237)
Observations	2,420	2,420	2,420
R-squared	0.705	0.585	0.689
Controls	Yes	Yes	Yes
Farmer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: Authors' calculations.

Note: Estimates from two-way fixed effects regressions with farmer and year fixed effects. Controls include aquaculture land, gender, age, years of education, flood exposure, and sample type. Robust standard errors clustered at the block level. *** p<0.01, ** p<0.05, * p<0.1.

ABOUT THE AUTHORS

Muhammad Nahian Bin Khaled (nahian@msu.edu) is a Ph.D. candidate in the Department of Agricultural, Food and Resource Economics, Michigan State University (MSU).

Mywish K. Maredia (maredia@msu.edu) is a Professor of Development Economics in the Department of Food and Resource Economics, MSU.

Sudha Narayanan (s.narayanan@cgiar.org) is a Senior Research Fellow in the Development Strategies and Governance (DSG) Unit of the International Food Policy Research Institute (IFPRI).

Ben Belton (ben.belton@cgiar.org) is an Associate Professor of International Development in the Department of Agricultural, Food and Resource Economics, MSU, and a Research Fellow in the DSG Unit at IFPRI.

Razin Iqbal Kabir (r.kabir@cgiar.org) is a Senior Program Manager in the Poverty, Gender, and Inclusion (PGI) Unit at IFPRI.

ACKNOWLEDGMENTS

The trial is registered with the AEA RCT Registry under RCT ID: AEARCTR-0013688. IRB approval was obtained from the International Food Policy Research Institute (IFPRI) Institutional Review Board (IRB) under IRB no. 00007490 and Michigan State Universi-ty (STUDY00010661). Local IRB approval was obtained from the Institutional Review Board of the Institute of Health Economics (IHEIRB), University of Dhaka, Bangladesh. We thank Evaluation and Consulting Services Ltd. (ECONS) and Desh Bangla SPF Hatchery Limited for assisting in data collection and program implementation, respectively. We acknowledge Mr. Alamgir Kabir, Mr. Asraul Haque Khan, Mr. Arifur Rahman, Mr. Tanzed Hossain, Mr. Shakil Kabir, and Mr. Abdul Zabbar Sakil for their excellent research assistance.

Funding for this work was provided by the CGIAR Trust Fund. This publication has been prepared as an output of the CGIAR Science Program on Policy Innovations, which is carried out with support from funders through their contributions to the CGIAR Trust Fund, and has not been independently peer reviewed. For details, please visit: https://www.cgiar.org/funders/. Any opinions expressed here belong to the authors and are not necessarily representative of or endorsed by IFPRI or CGIAR.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
A world free of hunger and malnutrition

IFPRI is a CGIAR Research Center

1201 Eye Street, NW, Washington, DC 20005 USA | T. +1-202-862-5600 | F. +1-202-862-5606 | Email: ifpri@cgiar.org | www.ifpri.org | www.ifpri.info