Technology Adoption and Quality Upgrading in Agricultural Supply Chains: A Field Experiment in Vietnam

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Abstract

We conduct a randomized experiment to examine the impact of technology training on technology adoption and quality upgrading in the dragon fruit supply chain in Vietnam. We randomly varied subjects of the training group across matched farmer-intermediary clusters—only farmers, only intermediaries, or both—and provided training on Good Agricultural Practices (GAP). We find strong evidence that insufficient knowledge and asymmetric information on quality between farmers and intermediaries have hindered technology adoption and quality upgrading. Specifically, we show three main results. First, training farmers increases the adoption of GAP technology and upgrades product quality as measured by compliance with international standards on pesticide residue. This suggests that insufficient knowledge may have hindered technology adoption. Second, jointly training farmers and intermediaries has an even stronger effect on farmers' technology adoption and quality upgrading. Third, we find no evidence of knowledge transfers from trained intermediaries to untrained farmers. The last two results together emphasize the role of asymmetric information on quality in hindering technology adoption and quality upgrading.

Keywords: Quality upgrading, technology adoption, agricultural supply chain, food safety (JEL codes: O12, Q12, Q13, L15)

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1 Introduction

Agricultural productivity in developing countries are significantly lower than that in developed countries (Caselli, 2005; Gollin, Lagakos, & Waugh, 2014). Despite the impressive growth in agricultural yields over the past half-century—largely due to the adoption of agricultural technologies such as hybrid seeds, fertilizers, and pesticides—supplying high-quality products remains a major challenge for many developing countries (World Bank, 2007). Although the globalization of agricultural trade has increased international awareness about food safety and quality (FAO, 2019)[1], studies have exposed constraints to quality upgrading from both supply and demand sides in agricultural supply chains in developing countries.[2]

This paper examines the impact of two potential constraints to quality upgrading. The first constraint is a lack of knowledge on technology—a supply side constraint. For instance, smallholder farmers mostly trade through local intermediaries at the farm gate with little interaction with exporters and multinational buyers (Fafchamps & Hill, 2005, 2008). This creates a communication barrier for farmers to learn about new technology, if the local intermediaries are incapable or have no incentive to educate farmers. The second constraint is the lack of trust on product quality driven by asymmetric information between farmers and intermediaries—a demand side constraint. Because quality verification of food products are costly and time consuming[3], intermediaries form an expectation on the quality based on the average product quality in the market which is low in developing countries. As a result, farmers may have low incentives to invest in quality upgrading technologies, confirming intermediaries' prior beliefs on low product quality.

[1]In December 2018, the United Nations General Assembly adopted a resolution to designate June 7th as World Food Safety Day.

[2]On the supply side, poor access to credit and financial services (Banerjee & Duflo, 2005; Beaman, Karlan, Thuysbaert, & Udry, 2015), informational inefficiencies (Hanna, Mullainathan, & Schwartzstein, 2014; Jack, 2013), and low quality of technology and inputs (Bold, Kaizzi, Svensson, & Yanagizawa-Drott, 2017) prevent farmers from adopting technology. On the demand side, weak contracting environment (Acemoglu, Antras, & Helpman, 2007; Antras, 2015; Blouin & Macchiavello, 2019; Krishna & Sheveleva, 2017), lack of access to export market (Atkin, Khandelwal, & Osman, 2017), and asymmetric information and seller reputation (Bai, 2018) are potential barriers to quality upgrading.

[3]In the case of fresh fruits and vegetables, the price of pesticide residue analysis at an ISO certified laboratory in Vietnam costs around US $150-$200 per sample.

The dragon fruit supply chain in Vietnam offers an ideal context to examine the impact of these two constraints on technology adoption and quality upgrading. Dragon fruit is a popular cash crop grown in several South-central provinces in Vietnam. In 2018, the country's growing area was around 53,000 hectares (approximately the size of 74,000 soccer fields) and Vietnam exported more than 1 million tons of dragon fruit in 2018, consisting one-third of total export value of Vietnamese vegetables and fruits (General Office of Customs, 2018). The fruit is mostly cultivated by smallholder farmers and sold to local intermediaries who then sell to local export enterprises or domestic market retailers.[4] Nevertheless, quality and food safety have shown to be a major barrier for exporting it to countries other than China.[5] Violations of pesticide residue limits in Vietnamese dragon fruit have been constantly documented in inspection reports from E.U. and U.S. (California Department of Pesticide Regulation, 2017; European Commission, 2014-2019).

To examine the impact of knowledge on agricultural technology and asymmetric quality information on quality upgrading, we first build a stylized model to characterize the interaction among farmers, intermediaries, and buyers along the dragon fruit supply chain. The model has several features related to quality provision. First, farmers have heterogeneous production efficiency that affects the costs of providing quality. Second, asymmetric information on quality exists between farmers and intermediaries and the latter have to infer quality from imperfect signals. The model delivers two key predictions on how improved knowledge on technology and asymmetric information on quality can incentivize farmers to adopt new technology and upgrade quality.

We conducted a field experiment with dragon fruit farmers and intermediaries in Vietnam to investigate the impact of these two constraints and test predictions from the model. The experiment randomly introduced a training intervention on Good Agricultural Practices (GAP), a set of agricultural management practices designed to improve food safety and

[4] Vietnamese dragon fruit is mainly supplied to the market as fresh fruit.

[5] Because of the high dependency to the Chinese market, the Vietnam government has been encouraging farmers and intermediaries to adopt production technologies and supply chain systems that comply with food safety standards mandated for entering the global value chain.

product quality.[6] The experiment was implemented across two major districts in Binh Thuan Province: Ham Thuan Bac and Ham Thuan Nam.[7] For this study, we partnered with the provincial government's agricultural research center, Binh Thuan Dragon Fruit Research and Development Center (BTDC), through which we randomly sampled farmer groups using a list of farmer groups registered with the research center. Each sampled farmer group was matched with intermediaries operating in the same commune and together formed a farmer-intermediary cluster. We randomly assigned each cluster to one of four groups: in the first treatment group, only farmers are provided training; in the second, only intermediaries are provided training; in the third, both farmers and intermediaries are provided training; and the fourth group is the control group in which no training was provided.

We contacted farmer groups and intermediaries to inform them that they were selected to participate in a study (without informing them about specific details about the treatments) in the fall of 2018 and invited them to a baseline survey and a three-day training program on GAP. In total, around 1,150 farmers and 230 intermediaries participated in the baseline survey and those who were eligible for training participated in the training sessions.[8] Agronomists specializing in dragon fruit from BTDC prepared customized class materials and led the three-day training sessions. The training sessions were provided at the cluster level to groups who were eligible to attend (e.g. in farmer training treatment groups intermediaries were not allowed to attend the sessions whereas in joint training treatment groups farmers and intermediaries both attended training sessions).[9] To raise efficacy, the training program was specifically designed by experts to support on-farm implementation of GAP in dragon fruit

[6]According to the Food and Agriculture Organization, GAP is defined as "a collection of principles to apply for on-farm production and post-production processes, resulting in safe and health food and non-food agriculture products, while taking into account economic, social and environmental sustainability." To ensure procurement of high-quality food products, a large number of importing countries and multinational buyers mandate agricultural producers and supply chains to comply with GAP standards (FAO, 2016).

[7]To account for geographical differences, we divided the two districts into 11 strata based on commune level divisions.

[8]Due to concerns with spillovers across treatment groups, in particular from treated to control groups, we also conducted surveys with four farmer groups outside the two districts of which the experiment was implemented. This provides another comparison group that we later use to test for spillovers.

[9]Because of the small size of intermediary only training groups, for logistical reasons, 3-4 intermediary only training groups were combined into one training class.

production. After training, we conducted two rounds of surveys, six months and twelve months after training respectively, to collect information on our outcomes of interest: GAP compliance, product quality, and farm gate sales of dragon fruit.

Consistent with the theoretical prediction, we find strong evidence that insufficient knowledge on technology and information asymmetry on product quality are significant barriers for technology adoption and quality upgrading in the dragon fruit supply chain. First, training farmers substantially increases technology adoption: farmers invited to the three-day training program increases GAP compliance by 6.1 percent from a baseline (control-group's) compliance rate of 0.72. This result indicates that, at least prior to the intervention, farmers lacked knowledge and technical skills to implement GAP technology in their farms.

Second, jointly training farmers and intermediares generates an even larger impact on farmers' technology adoption: GAP compliance rises by 9.2 percent and lasts for at least 12 months after receiving training. One possible explanation for why joint training had a larger effect than farmer only training is that the training program provided an opportunity for farmers and intermediaries to communicate with each other, establish relationships, and build trust. Studies suggest that trust between buyer and seller is essential for quality provision in the absence of contracts (Bai, 2018; Björkman-Nyqvist, Svensson, & Yanagizawa-Drott, 2018). Accordingly, through participating in joint programs farmers and intermediaries can build relationships that mitigate the problem of asymmetric information and incentivize farmers to adopt quality upgrading technologies. Another possible explanation is potential diffusion of knowledge from intermediaries to farmers, which strengthens the effect of training.

Interestingly, however, we find no evidence of knowledge diffusion from intermediaries to farmers. Although we do find that the intermediaries knowledge about GAP increases after receiving training, such knowledge does not transfer to farmers who did not receive the training, even when the farmer and intermediary are in the same treatment cluster. This result suggests that the strengthened effect of joint training on technology adoption and quality upgrading is because it helps resolving the problem of information asymmetry and trust on quality at least partly.

In a smaller random sample in which we hired an ISO-certified laboratory to test the product quality (18 different types of pesticides or active ingredients), we find a strong positive effect of GAP training on product quality. Among the 264 samples tested for pesticide residue, the farmer-only training and joint training reduce the incidence of violating the Maximum Residue Limit (MRL) set by European Commission by 14 percent and 21 percent, respectively.[10] The positive effect of training on quality upgrading suggests that insufficient knowledge on technology may have hindered quality upgrading. Moreover, the larger magnitude of the effect of farmer-intermediary joint training relative to farmer only training implies the importance of information asymmetry and/or lack of trust as a barrier in promoting quality upgrading.

In comparison, when we use China's MRL instead of E.U.'s MRL to determine compliance with food safety we find zero treatment effects. The reason is that compared to E.U. or U.S., China has set high tolerance levels or MRLs which are easier to comply to. Given the high export volume to China, this may explain why dragon fruit farmers have little incentive to upgrade product quality in the first place.[11] Moreover, we find no significant effect of GAP training on other product attributes – sweetness, appearance, or size of the fruit. This is not surprising since GAP is designed as a quality enhancing technology that promotes food safety and prevents usage of toxic chemical pesticides. Note that previous studies in agricultural technology adoption mostly focused on technologies that enhance quantitative aspects of production. Thus, our evaluation on the impact of training GAP technology offers a novel feature to understanding technology adoption behavior.

An important question is: do technology adoption and quality upgrading actually improve farmers' sales and profits? Our model predicts that both training and reduction in information

[10] A maximum residue level (MRL) is the highest level of a pesticide residue that is legally tolerated in or on food or feed when pesticides are applied according to GAP. The tolerance value may differ across countries according to their regulation. For example, United States and Europe have set MRLs that are lower then that set by Japan or China.

[11] Though one can argue the other way around such that low product quality is the reason for high export to Chinese market.

asymmetry leads to higher prices. In our empirical analysis, we find significant increases in export activities to high-price countries for farmers who received joint training; but we find no significant change in exports for farmers who received training without intermediaries. In addition, joint training group farmers receive 10.3 percent higher price at the farm-gate and earn 16-45 percent higher revenue than farmers in the control group. Nonetheless, we do not see significant increases in seasonal or annual profits among farmers in joint training groups (the coefficient suggests a 20 percent increase in annual profits but lacks precision to be statistically significant). This can be partly explained by the increase in expenditure for purchasing inputs—specifically, we find that farmers with joint training spent more on pesticide and facility—which offsets the gains in revenue.[12]

This article contributes to the broad literature on agricultural technology adoption. The literature discusses several barriers to technology adoption, including market inefficiencies, credit and risk constraints, informational problems (see Jack (2013); Knowler and Bradshaw (2007); Magruder (2018) for excellent reviews on the literature), and behavior biases (Duflo, Kremer, & Robinson, 2011). Most studies find that training interventions significantly increase knowledge but show mixed evidence of impacts on production outcomes, such as yield and revenue.[13] Our paper is in line with these studies by providing knowledge and training on an agricultural technology expected to enhance farming outcomes. However, unlike previous studies that mainly focused on improving the quantity of output, we contribute to this literature by studying the use of training on technologies that improve the quality of output. In addition, we also complement this literature by providing evidence on the effect of training

[12] One possible reason for the low net payoffs of quality upgrading to farmers is the market structure in the dragon fruit supply chain. The supply chain features many smallholder farmers, a number of small local intermediaries or middlemen purchasing from farmers and selling to exporters, and a few export enterprises who have the ability to sell to certain overseas markets such as E.U., U.S. or Japan. We plan to examine the implication of this type of market structure on technology adoption and quality upgrading by extending our current model in a later version.

[13] Prior experimental work has established field schools (Davis et al., 2012; Feder, Murgai, & Quizon, 2004; Godtland, Sadoulet, de Janvry, Murgai, & Ortiz, 2004; Van den Berg & Jiggins, 2007) or offered training programs (Grimm & Luck, 2020; Kondylis, Mueller, & Zhu, 2017; Vasilaky, Toyama, & Baul, 2018) to educate farmers on certain cultivation techniques. Others have explored methods relying on ICT (Aker, 2011; Casaburi, Kremer, Mullainathan, & Ramrattan, 2014; Cole & Fernando, 2020) to provide agricultural advice to mainly farmers.

intermediaries and speaking to the role of supply chains in diffusing agricultural technology.

Our paper is also related to the growing literature on quality provision in markets with asymmetric information on product quality. When quality is unobservable by buyers, lack of feasible and enforceable contracts makes producers subject to the hold-up problem (Krishna & Sheveleva, 2017) which restrains producers from offering high quality products (Macchiavello & Morjaria, 2015). In such settings, producers may have to establish reputation through repeated transactions with buyers which takes time and requires up-front investment. This may be even more challenging in developing countries due to reasons such as financial constraints and collective-reputation effect (Bai, Gazze, & Wang, 2019; Björkman-Nyqvist et al., 2018; Bold et al., 2017; Zhao, 2018). For example, Bai (2018) finds the role of branding technologies in mitigating consumers' mistrust and improving sellers' quality provision in a Chinese watermelon retail market. While these papers highlight the dynamic feature of consumer learning and reputation building during the final transaction stage (i.e. buyer is most likely the final consumer), our study takes information problem as given and investigates how it affects the technology adoption and quality provision during the production stage.

The rest of the paper is organized as follows. The next section provides context on food safety and the agricultural supply chain. In section 3, we lay out the theoretical framework and derive predictions on the impacts of two constraints. We describe the experimental design and details of the data in section 4. Section 5 presents the empirical analysis where we estimate effects of training on technology adoption, quality upgrading and market performance. Section 6 concludes the paper.

2 Background and Setting

2.1 Food Safety and Quality

Agrochemicals, such as fertilizers and pesticides, have become integral inputs for many agricultural systems. For instance, Erisman, Sutton, Galloway, Klimont, and Winiwarter

(2008) estimate that 48 percent of the global population depend on food produced through synthetic nitrogen fertilizers which provide essential nutrients to enhance the growth of plants. Pesticides, which include insecticides, fungicides, herbicides, and plant growth regulators, also play an important role by protecting crops from insects, fungi, weeds, and diseases.[14] Despite the benefits of agrochemicals, concerns over abuse and misuse of chemical pesticides have been growing across the world prompting governments and multinational organizations (e.g. FAO and U.N.) to take action and require food producers to implement safety measures to monitor and regulate the use of toxic pesticides.

Currently, most developed countries heavily enforce pesticide residue testing on imported food products to ensure food safety and compliance with proper use of pesticides. In accordance with this, we treat pesticide residue as a key measure of food quality and provide an accurate measure based on laboratory tests. Moreover, Good Agricultural Practices (GAP) is widely endorsed by governments and industries as a farm management system that helps food producers to protect their plants and crops without excessively relying on toxic pesticides. Thus, our intervention on GAP training provides pragmatic knowledge and technology for upgrading food quality.

2.2 Pesticide Use in Vietnam

Pesticide use in the Vietnamese agricultural sector has drastically increased. Statistics show that annual pesticide consumption rose from 35,000 tons in 2002 to 105,000 tons in 2012 (Institute of Legistration Study, Vietnam, 2013). During the same period, the number of formulated pesticides registered with the Ministry of Agriculture and Rural Department (MARD) have increased by nearly sixfold, respectively (Hoi, Mol, & Oosterveer, 2013). What is particularly alarming is that pesticides of high toxic categories have shown the greatest

[14] The Food and Agricultural Organization (FAO) defines pesticide as any substance or mixture of substances intended for preventing, destroying, or controlling any pest during the production, processing, storage, and transport. It also includes substances intended for use as a plant growth regulator, defoliant, or preventing premature fall of fruit or deterioration during storage and transport.

increase in registered formulated pesticides.[15] For instance, between 2002 and 2013, the number of formulated pesticides categorized as moderately hazardous (category II) and slightly hazardous (category III) have each increased by sevenfold and fivefold, respectively.[16]

According to a survey with Vietnamese farmers, up to 80 percent of agricultural pesticides are used incorrectly, causing increased production costs and greater toxic load in the environment and in agricultural products (Nguyen, Le, Havukainen, & Hannaway, 2018). For example, a survey in Thai Binh province in 2014 found that 80 percent of the farmers violated proper use of pesticides and 70 percent did not comply with the recommended pre-harvest interval during which pesticide use should be avoided (Lan, Le, & Phong, 2014). In Binh Thuan province, a government inspection report shows that 14 out of 59 fruit and vegetable samples contained pesticide residue exceeding allowed tolerance levels, or maximum residue limits. Notably, residues of Carbendazim, a pesticide forbidden to be sold and used in agriculture in Vietnam but widely used in dragon fruit production, was found in 12 out of 14 samples (BTPPD, 2019).

Contributing to this major problem is the continued presence of low-quality and counterfeit pesticides on the market.[17] According to statistics by the Vietnamese government, these products account for 10% of the total pesticides distributed and used in Vietnam (Institute of Legistration Study, Vietnam, 2013). In reality, these pesticides could have an even larger market share, as illegal pesticides are not included in government statistics. There is profound evidence of selling low-quality or illegal pesticides in Vietnam.[18] For instance, in 2018, the

[15] According to the World Health Organization (WHO) Classification of Pesticides by Hazard, Ia = extremely hazardous, Ib = highly hazardous, II = moderately hazardous, III = slightly hazardous, U is unlikely to present acute hazard (WHO, 2010).

[16] In 2013, around 60% of formulated pesticides were either moderately or slightly hazardous. In contrast, the number of formulated pesticides that are unlikely to present an acute hazard (category U) merely doubled and accounted for only about 15% of all formulated pesticides.

[17] In a recent study on fertilizer markets in Uganda, (Bold et al., 2017) show that fertilizers sold at local retail shops have far less nitrogen content than authentic fertilizers.

[18] In 2007, more than 21 tons of illegal pesticides were confiscated by PPD inspection teams (Vinachem National conference on plant protection activity of 2007 and planning activity for 2008). Moreover, 13 out of 83 inspected pesticides on the market violated labeling and quality regulations, and 12 percent of 5,347 inspected pesticides companies and retailers were found to violate pesticide regulations such as selling illegal pesticides (Quyen T, Disorder of pesticide market). A report in 2015 shows that 1,704 out of 12,347 pesticide retailers sold poor quality and illegal pesticides.

Vietnam Steering Committee Against Smuggling, Trade Frauds and Counterfeiting Goods, reported 306 violations out of 1,420 cases of selling expired, fake and illegal pesticides (Hue, 2019).

The prevalence of low-quality pesticides on the market contributes to the overuse of pesticides or the use of pesticide cocktails by farmers (Hoi, Mol, & Oosterveer, 2009; Hoi, Mol, Oosterveer, van den Brink, & Houng, 2016; Mattah, Mattah, & Futagbi, 2015; Schreinemachers et al., 2015; Yan, 2012). In addition, with numerous formulations of different pesticides on the market, farmers are induced to heavily rely on pesticide retailers for information on efficacy and utilization. However, a large percentage of pesticide retailers are reported to have insufficient technical knowledge on pesticide use (HanoiDARD, 2013). Moreover, since advanced and more recently formulated pesticides often have lower retail profit margins compared to cheap, low-quality or counterfiet ones, retailers may instruct farmers to use counterfeit or illegal pesticides (Anh, 2013; Hoi et al., 2009).

2.3 Dragon Fruit

Dragon fruit (its scientific name is *Hylocereus andatus* and better known as *pitaya* in South America and *thanh long* in Vietnam) was first introduced into Binh Thuan province, Vietnam by catholic priests from South America in the late twentieth century. The plant is a cactus species grown in tropical regions as an ornamental plant or fruit crop. The fruit has a bright red skin studded with green scales (thus, the name dragon fruit) and a white, juicy flesh with black seeds (see Appendix Figure A-1 for picture of dragon fruit). As a perennial fruit crop, farmers usually harvest the fruit twice a year - once during the dry season (October - February) and once during the wet season (March - September).

Vietnam has an economy that is dependent on agriculture and is also the leading producer and exporter of dragon fruit in the world.[19] The country exports 80-85 percent of its national

[19]In the year 2018, agriculture, forestry and fishing absorbs 37.3 percent of Vietnamese employed population, the highest share among all economic activities. And it is also the second largest contributor to gross domestic product, accounting for 15 percent. Data from *General Statistics Office Of Vietnam* https://

output of dragon fruit (BTDC, 2019). In 2018, dragon fruit consisted one-third of total export value of Vietnamese vegetables and fruits (General Office of Customs, 2018). Table 1 shows the volume, value, and prices of Vietnamese dragon fruit exported to ten countries with highest export volume in 2015 and 2019. China is the largest export market, accounting for 94 percent in export volume in 2015 and 99 percent in 2019. Other export markets all together consisted only approximately 1 percent of volume and 2 percent of value in 2019. Yet, average unit price of exports to several countries (Canada, Japan, South Korea, Netherlands, and United States) were three-seven times higher than that of exports to China. This pattern of low share to high mark-up market is also observed in other perishable agricultural products (see Appendix Table A-1). The fact that Vietnam and China share a land border may facilitate exporting to China, resulting in timely and low-cost shipping to China. For almost all other countries, air freight is the only option for shipping perishable fresh fruit and vegetables. However, it is hard to explain the huge price differences based on transportation cost alone.

Besides the difference in transportation cost, the Chinese market considerably differs from other markets in terms of regulations on food safety and pesticide use. As we show below, China's tolerance levels for chemical pesticides in food are several times higher than those imposed by other developed countries. More importantly, food safety inspections are not strictly enforced at the Chinese border check points (Trinh et al., 2018). In contrast, most developed countries impose painstaking standards and procedures to conduct food safety inspections of imported products at their borders. Strict enforcement of import restrictions can cause a challenge to agricultural supply chains in developing countries. Producers may lack information on the importing country's regulations on food safety and, furthermore, lack production skills required to comply to those standards. Also, traders are likely exposed to the risk of inspection failures and profits losses due to shipment rejections at the importing country's border.

www.gso.gov.vn.

In fact, recent inspections in Europe and U.S. on dragon fruit imports from Vietnam show violations in pesticide residue levels, raising concerns on its quality and consumer safety. For example, the European Commission's Rapid Alert System for Food and Feed (RASFF) reports 19 cases of rejections of dragon fruit shipments from Vietnam at the border due to detection of pesticide residue levels exceeding limits set by the European Union (European Commission, 2014-2019). In a 2017 inspection report, the California Department of Pesticide Regulation found illegal pesticide residue levels in 100 percent of samples of Vietnamese dragon fruit exports (California Department of Pesticide Regulation, 2017). Agricultural experts point out that abuse of chemical pesticides and growth regulators during the on-farm production stage is a major factor hindering the production of high-quality dragon fruit (Trinh et al., 2018). Alerted by these incidents, Vietnam's Ministry of Agriculture and Rural Development has been calling out to the agricultural community to take immediate action to manage pesticide use and reduce the use of highly toxic pesticides.

2.4 Dragon Fruit Supply Chain

The experiment was implemented in Binh Thuan province, which accounts for 55 percent of national production of dragon fruit in Vietnam (BTDC, 2019). Figure 1 illustrates the dragon fruit supply chain in Binh Thuan province. There are three main layers in the supply chain: farmers, intermediaries, and buyers. Dragon fruit production in Binh Thuan province is dominated by smallholder farmers, who each typically cultivates less than one hectare of farm area. Intermediaries can be classified as either local collectors or exporting enterprises. Local collectors play the role of middlemen who search for farms that are ready for harvesting, purchase fruits from the farmers and sell them to export enterprises or domestic retailers.[20] Export enterprises operate packing facilities at which fruits are cleaned, packed, and prepared for shipping. Most Chinese and international buyers purchase from export enterprises while

[20] A study with dragon fruit farmers in Tien Giang province, another major dragon fruit growing region, shows that farmers mostly trade with local collectors and rarely sell directly to export enterprises or international buyers (Sakata & Takanashi, 2018).

a few local cooperatives trade directly with international buyers. Domestic retailers purchase fruit from farmers and local collectors and supply to the domestic market.

Most trade at the farmer-intermediary level occur without a formal contract. Farmers and intermediaries start bargaining right before the harvest. During the bargaining stage, collectors make a price offer based on a grading criteria which largely depends on certain exterior features of the fruit, such as the condition of the skin and size. However, as markets differ in desired product features the grading criteria also varies across different markets. For example, the highest grade for the Chinese market requires the fruit to have a bright red color with no defects on the skin and weigh approximately 0.5 kilograms. For European or other Asian markets the fruit's skin color or size is not as important as compliance with food safety standards required at the destination market. When the farmer and intermediary reaches an agreement, the intermediary hires laborers for harvesting and transports harvested products to packing facilities. The fruit may be additionally sorted into different grade categories during harvesting and processing. High-graded products are then shipped off to overseas buyers while low-graded products are sold to domestic buyers.

In the supply chain, smallholder farmers mostly trade through local intermediaries at the farmgate with little interaction with exporters and multinational buyers (Fafchamps & Hill, 2005, 2008). This creates a communication barrier for farmers to learn about new technology, if the local intermediaries are incapable or have no incentive to educate farmers. Moreover, the information asymmetry on product quality between farmers and intermediaries, and the resulting lack of formal contract, further discourage farmers from investing to adopt the quality-upgrading technology. In the rest of the paper, we first develop a model of qualty upgrading under asymmetric information and then empirically investigate the impact of the two constraints, the lack of sufficient technology knowledge and asymmetric information on quality, on farmers' decisions to adopt quality-enhancing technology.

3 Theoretical Framework: Quality Provision under Asymmetric Information

In this section, we provide a theoretical framework characterizing the interaction between farmers and intermediaries. The aim of this section is to deliver predictions on farmers' export decision, quality provision and price that can be tested in our empirical setting. More specifically, we provide hypothetical impacts of either supply side constraint-increase in knowledge-or demand side constraint-improve asymmetric information on product quality. The first predicts about our first intervention of training and the second about our second intervention of joint group.

The model has two key features. First, farmers have heterogeneous productivity: more efficient farmers produce quality at lower cost. Second, there is asymmetric information on quality: intermediaries cannot directly observe quality, making them subject to the risk of inspection failures and profits losses. The proofs in this section are relegated to Appendix D.

3.1 Setup

Environment Farmers are endowed with quality (more specifically, food safety) related efficiency $k \in [\underline{K}, \bar{K}]$, which follows probability density function $g(k)$. There are two types of intermediaries, local type who sell to domestic or low-markup export market (together we call "local" market) and export type who have access to high-markup export market. Intermediaries are initially local type and they can choose to upgrade with cost f. This represents the cost of relationship management, up-front investment in equipment etc.

Timeline There are two periods. At the first farming stage, each farmer grows one unit of output. Farmers first decide whether to target at local market with no cost or at high-markup export market with cost s. s represents the market access barrier and includes learning cost of acquiring export standard and quality enhancing technologies, pecuniary cost to purchase facilities and equipment and other cost such as contacting export enterprises etc. After choosing target market, they decide quality related input i to put into production. Meanwhile, intermediaries make upgrade decisions.

At the second harvest stage, both local and export intermediaries visit farmers at the farm gate. They simultaneously decide price p and the number of farmers to contact v. Farmers sell to the intermediaries who offers highest price. After purchasing from farmers, intermediaries source the products to the corresponding target market.

Markets For the final market, local market purchases all quality at price P^D. High-markup export market only accepts qualified product. They will take one sample from the output pool and purchase at P^E only if the sample quality is above standard Q^*. There is no quality premium once it passes the threshold. Due to the ease to perish, products rejected by high-markup export market cannot by resold to other markets and intermediaries bear all the losses from the rejection.

For the middle market where intermediaries and farmers interact, we make the following assumptions. First, we simplify market for local intermediaries as perfect competition. Second, due to, for example, limited information technology, farmers are unable to know the price of each export intermediary, leading to search and match frictions. We follow static search framework by Mortensen (2003) to characterize market for export intermediaries. We make standard assumptions that for a large enough market, price offers from export intermediaries arrive at farmers according to Poisson process with mean θ, which is the level of intermediation. The distribution over the number of offers received per farmer z is given by

$$Pr(z) = \frac{e^{-\theta}\theta^z}{z!}$$

Third, for the current stage, we simplify the model by assuming that export intermediaries offer uniform price to all farmers. [21]

[21] We are going to extend and enrich the model to allow for pricing based on imperfect signals on quality. Higher signal implies better underlying true quality, thus lower rejection rate and intermediaries have higher willingness to pay. Previewing the empirical results, we find evidence on the presence of quality premium in figure 4. In joint training group, higher compliance is associated with higher price.

Quality and Signaling Quality depends on efficiency k and input i.

$$q(k,i) = ki$$

Quality is known by farmers as they know their efficiency and the amount of input. It is also observable to export market as products have to go through food safety inspection at the custom when imported. However, it is unobservable to intermediaries since they do not have enough knowledge about export regulations and cannot afford the testing equipment. They instead infer from a signal q', which can be observable characteristics like skin color that are imperfectly correlated with underlying quality. The signal is randomly drawn from normal distribution with mean of true quality q and standard deviation σ. Export intermediaries accept the product only if its signal exceeds the quality standard, $q' \geq Q^*$. Then the probability of product with quality q being accepted, denoted as $\Phi(q)$ is increasing in its true quality

$$\Phi(q) := Prob(q' \geq Q^*|q) = 1 - \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{Q^*} e^{-\frac{(t-q)^2}{2\sigma^2}} dt$$

Finally, we assume farmers' cost of input and intermediaries' cost of offers are quadratic. $c(i) = \frac{1}{2}i^2, c(v) = \frac{1}{2}v^2$.

3.2 Equilibrium

Intermediaries problem Intermediaries make decisions on first upgrading and second price offers. Local intermediaries will offer price P^D as they are perfectly competitive. For export intermediaries, they follow a mixed strategy, choosing price p from range $[p^{\min}, p^{\max}]$. The distribution of price offers, denoted as $F(p)$ is as follows

$$F(p) = \frac{1}{\theta} \ln(\frac{\beta P^E - P^D}{\beta P^E - p}), p \in [P^D, (1 - e^{-\theta})\beta P^E + e^{-\theta} P^D] \tag{1}$$

where β is export intermediaries' expectation about quality. More specifically, it is the probability that the sample satisfies the quality standard, or in other words, the proportion of qualified product. As market becomes more competitive (θ increases), export intermediaries are more likely to propose high prices to beat other competitors.

Prior to entry, farmers take optimal pricing decision as given and compare the expected profit in two markets. The free-entry level of intermediation is given by

$$\theta = \ln(\frac{\beta P^E - P^D}{\sqrt{2f}}) \tag{2}$$

There is no export intermediaries if they expect quality is lower than $\frac{P^D}{P^E}$.

Farmers' problem Farmers first decide whether to enter high-markup export market then choose the amount of quality related input.

Conditional on having made entry decision, farmers targeting at local market will input nothing as quality is not rewarded in these markets. Farmers targeting at high-markup export who has efficiency k and expect to get $E(p)$ from export intermediaries will choose the quality $q(k, E(p))$ such that the marginal return to improving quality equals the marginal cost.

$$\frac{q(k, E(p))}{k^2} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(Q^* - q(k,E(p)))^2}{2\sigma^2}} (E(p) - P^D)$$

where

$$E(p) = [1 - e^{-\theta}(1+\theta)]\beta P^E + e^{-\theta}(1+\theta)P^D$$

. More efficient farmers will produce higher quality as marginal return is the same for all farmers while the marginal cost is lower for more efficient farmers.[22] The marginal farmers who produce just qualified product have the following efficiency level.

$$k^q(E(p)) = \sqrt{\frac{\sigma\sqrt{2\pi}Q^*}{E(p) - P^D}} \tag{3}$$

[22]Technically, $\frac{\partial q(k,E(p))}{\partial k} > 0$ is implied by second order condition $\frac{\partial^2 U}{\partial q^2} < 0$.

Farmers with efficiency above will supply qualified product and those below provide unqualified once entering the export market.

Prior to entry, farmers compare the expected profit in two markets and decides target market. As more efficient farmer benefit more from entry, [23] there exists a cutoff $k^{ex}(E(p))$ such that farmers with efficiency higher than the cutoff target at high-markup export market and those with efficiency lower target at local market.

$$\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{Q^*} e^{-\frac{(t-q(k^{ex}(E(p)),E(p)))^2}{2\sigma^2}}dt(E(p)-P^D)-\frac{1}{2}(\frac{q(k^{ex}(E(p)),E(p))}{k^{ex}(E(p))})^2=s \tag{4}$$

Equilibrium We want to solve for farmers' market decision k^{ex} and quality choice k^q, intermediaries' price offer $E(p)$ and upgrade strategy θ. In equilibrium, belief β is consistent with true distribution of product quality on the export market. With slightly misuse of notation, let β represent the true quality composition for the rest of the paper.

Demand constraint specifying the intermediaries' optimal price given farmers' quality provision is obtained by incorporating level of intermediation into expected price.

$$E(p)=\beta P^E-\sqrt{2f}(1+\ln\frac{\beta P^E-P^D}{\sqrt{2f}}),\beta\in[\frac{P^D}{P^E},1] \tag{5}$$

If proportion of qualified product β increases, intermediaries offer higher prices.

For supply side constraint, there are two possible cases: when there is exclusively qualified product and when unqualified product show up and contaminate the quality pool on the high-markup market. Given export intermediaries' pricing strategy, farmers will make entry and production constraint such that the quality composition on the high-markup export

[23] By envelope theorem, $U_k(E(p),k,i(k,E(p)))>0$.

market is

$$\beta = \begin{cases} \dfrac{\int_{k^q(E(p))}^{\bar{K}} \Phi(q(k, E(p)))g(k)dk}{\int_{k^{ex}(E(p))}^{\bar{K}} \Phi(q(k, E(p)))g(k)dk} & \text{, if } k^q(E(p)) > k^{ex}(E(p)) \\ 1 & \text{, if } k^q(E(p)) \leq k^{ex}(E(p)) < \bar{K} \end{cases} \tag{6}$$

Combining both supply and demand, we can pin down equilibrium price and quality.

3.3 Testable Predictions

The model generates several testable predictions. The first two are based on current high-markup export market containing both qualified and unqualified product while the last is conditional on high-markup market containing only qualified product. Prediction 1 shows the effects of supply side constraint and prediction 2 states those of demand side constraint.

Prediction 1. *If training improves farmers' efficiency k, then price increases, more farmers export to high-markup market and quality improves.*

When farmers become more efficient, the marginal return of improving quality increases and outweighs the cost. Hence farmers upgrade quality. Expecting higher quality, export intermediaries are willing to offer higher prices. This in turn raises the attractiveness of high-markup export market, new entrants who used to target at local market now switch high-markup export market.

Prediction 2. *If degree of asymmetric information σ decreases, price increases, fewer farmers export to high-markup market and quality improves.*

When signal is more accurate, low efficiency farmers who supply unqualified product are more likely to send bad signal and be rejected by export intermediaries. In that case, they have less incentive to enter high-markup export market. In contrast, high efficiency farmers who supply qualified product are more likely to draw good signal. The benefit of improving quality increases and exceeds the cost and they have stronger incentive to input more and upgrade quality. These two effects jointly levers up the quality on the high-markup export market. And export intermediaries raise prices accordingly.

Prediction 3. *If current high-markup export market contains exclusively qualified product, then training and improvement in signal structure have the same effects: price does not change, more farmers export to high-markup market and quality improves.*

When product on high-markup export are all of high quality, then the prices are fixed as the quality composition (proportion of qualified product is one) does not change. All of these changes increase the return of quality upgrading and market upgrading. More farmers explore the high-markup market option and improve quality provision.

4 The Experiment

4.1 Experimental Design

We originally designed a field experiment with two cross-randomized interventions, resulting in a 4×2 factorial design. Figure 2 provides an overview of the timeline and interventions of the original experiment. According to the design, the first intervention offers training on Good Agricultural Practices (GAP) and the second intervention offers eligibility to farmer groups to apply for the VietGAP certificate. In this paper, we focus on evaluating the effect of the first intervention and examine the effect of the second intervention in a separate study.[24]

To implement the interventions, we partnered with Binh Thuan Dragon Fruit Research and Development Center (hereafter, BTDC), operated by Binh Thuan's provincial government. BTDC was an ideal partner for collaboration as it conducts research on dragon fruit production, provides extension services to farmers, and operates audit/certification programs in the region. Moreover, agronomists and dragon fruit experts at BTDC adapted GAP for dragon fruit

[24]The separate study utilizes another randomized control trial in the same context of this paper where we exogenously vary the testing agency for pesticide residue testing to evaluate how testing credibility affects the value of certification.

farming and developed manuals and materials for training. In collaboration with BTDC, our project was able to provide GAP training programs to farmers and intermediaries across two major districts of Binh Thuan province (Appendix Figure A-2 presents a map of Binh Thuan province with the two districts highlighted).

GAP is composed of five on-farm management sectors: 1) Production area and tool, 2) Hygiene and work safety, 3) Soil, Water and Waste, 4) Pesticide, and 5) Fertilizer. The training material laid out a practical step-by-step guide for implementing and monitoring GAP in the field along these five sectors. In addition, trainees were provided with a GAP checklist which was later used for auditing compliance with GAP.[25] The English version of the GAP checklist is provided in Appendix Figure A-3.

Training sessions were instructed by BTDC staff. Training materials and information on pesticide management were designed specifically for implementing GAP in dragon fruit farming.[26] Accordingly, a key component of the training course was providing information on food safety and proper purchase, use, and storage of chemicals and pesticides. More specifically, trainees were informed about which pesticides are permitted or banned for use in dragon fruit farming, how to treat certain diseases and pests common to dragon fruit, proper handling of chemicals and pesticides, and detailed instructions for pesticide application throughout the production cycle. Participants went through an intensive 3-day training program which included lectures, focus group discussions, and was followed by a field demonstration by our experts on the last day of training. After the last training session, participants received small compensations in the amount of 100,000 Vietnamese Dong (approximately 4.3 US Dollars).

Importantly, the training program was offered in three different group compositions: (i) Farmer training group – only farmers were invited to receive GAP training, (ii) Intermediary training group – only intermediaries were invited to receive GAP training, and (iii) Joint

[25]The GAP checklist used for this study, which has 32 items, is an abbreviated version of the full VietGAP assessment.

[26]For instance, proper application of pesticides for farm production, such as type of pesticide, timing and dosage to apply, vary by crop and season.

training group – both farmers and intermediaries were invited to receive GAP training. We did not offer GAP training to farmers and intermediaries in the control group although we provided general information on food safety and the importance of proper pesticide use in producing high-quality dragon fruit. After the baseline survey, all treatment and control groups had a one-time group meeting in which both farmers and intermediaries gathered to introduce themselves and participated in several lab-in-the-field experimental games.[27]

To sum up, the intervention under the study of this paper involves two treatments which are intended to evaluate the effects of two constraints to quality upgrading. The first training treatment aims to resolve supply side constraint–lack of knowledge. The second joint treatment is designed to alleviate demand side constraint–low trust and information asymmetry–by offering opportunity for farmers and intermediaries to actively interact, and thus establish trust. Our theoretical framework in section 3 provides predictions of these interventions on technology adoption and quality upgrading. Prediction 1 suggests that farmers receiving training treatments adopt the technology and increase the product quality. Prediction 2 suggests that farmers jointly trained with intermediaries show higher magnitude of improvement in quality provision.

4.2 Sample Selection Details

4.2.1 Farmer Group Selection

The unit of sample selection for farmers is a farmer group, consisting of around 15 farmers per group. There are several reasons that makes farmer groups ideal as our unit of treatment group. First, farmer groups are self-organized and composed of farmers located in the same town. Thus, it is likely for learning and spillovers to occur within a group. By assigning treatment at the level of farmer groups we are allowing for intra-group learning on a technology which may increase technology adoption and, at the same time, reduce potential treatment

[27] Games include the dictator game, trust game, and double-oral auction game where participants were randomly divided into buyers and sellers.

spillovers across groups given the group organization and geographic characteristics. Second, previous government support and policy interventions have been provided at the farmer group level. We follow this convention by providing training at the farmer group level. Finally, according to government regulations, farmer groups have to be registered with BTDC in order to receive any assistance from the government. Therefore, by partnering with BTDC we were able to use the list of registered farmer groups in two major districts – Ham Thuan Bac and Ham Thuan Nam – as the pool for random sampling. We found 406 registered farmer groups with approximately 8,670 farmers across 23 communes.

4.2.2 Intermediary Selection

Unlike farmer groups, there was no available list of dragon fruit intermediaries operating in the study area. To create a list of intermediaries, in August 2017, we carried out a search and recruitment drive in the two districts. Enumerators searched all major roads and used information on the company sign or the presence of a collection facility to identify dragon fruit intermediaries. When identified as an intermediary handling dragon fruit the enumerator recorded geo-referenced information. In total, we found 325 dragon fruit intermediaries operating in the area among which 228 expressed interest to participate in this study when contacted in August 2018.[28] Using all 228 intermediaries willing to participate in the study we matched them with a farmer group to form a cluster, serving as the unit of randomization for treatment assignment. Clusters were formed by matching intermediaries with a farmer group located in the same commune; if there was no farmer group left to match within the same commune then the intermediary was matched with the geographically closest farmer group within the same strata.

[28] To incentivize intermediary participation BTDC offered to support intermediaries with registering to the supply chain database that was planned to be launched in 2020 by the Vietnam government.

4.3 Randomization

For treatment assignment, we constructed 11 geographical strata by combining 23 communes in the two districts.[29] Treatments were randomized within each strata at the farmer-intermediary cluster level where each cluster consists of one farmer group and around three intermediaries. Our main sample consists of 88 clusters. We additionally sampled four farmer groups from two communes outside the two districts and assigned them to control to serve as a spillover-proof control group. Out of 88 clusters, we randomly selected 66 clusters (6 clusters from each strata) and assigned them to one of the three training treatment groups: farmer training (22 clusters), intermediary training (22 clusters), and joint training (22 clusters). The remaining 22 clusters were assigned to the control group.[30]

4.4 Data Collection

We collect multiple rounds of data at around six-month intervals starting with the baseline survey. In total, we conducted three rounds of in-person interviews with farmers (a baseline survey and two follow-up surveys) and two rounds of in-person interviews (a baseline survey and the first follow-up survey) and one round of phone interview with intermediaries (second follow-up survey).[31]

The baseline survey took place right before the training intervention in winter 2018. Farmers were asked questions on (a) demographic and farm characteristics, (b) farm production and sales to intermediaries, (c) expenses on farm inputs, (d) self-reported compliance with GAP, and (e) cognitive and noncognitive abilities. The intermediary survey was administered to the representative of each firm, who was often the owner or office manager of the firm.

[29] The reason for combining communes is because several communes had only two to five registered farmer groups.

[30] For assignment to the second intervention, one cluster from each training group and strata (11 clusters within each training treatment group) was assigned to the certification treatment and the other cluster was assigned to without certification.

[31] We conducted phone interviews with intermediaries in the second follow-up survey due to the outbreak of covid-19. At the time of the second follow-up survey our local partner, BTDC, had to conduct surveys in accordance with the government's covid-19 prevention measures. Accordingly, they had decided to conduct in-person interviews with individual farmers but phone interviews with intermediaries.

We asked questions on (a) firm characteristics, (b) trading and export activities, and (c) self-reported compliance with GAP in the packing and processing stage.

Followup surveys were administered approximately six months and twelve months after the training intervention. Extension staff at BTDC visited farmers and intermediaries to conduct individual interviews. Each round of followup survey with farmers included a basic module, which asked to report on farm production and transactions with intermediaries, a product assessment module, and an on-farm GAP audit module. The product assessment module was intended to measure observable (defined as verifiable at the site) product characteristics of the fruit along four main dimensions - (a) sweetness, (b) appearance (skin color and bract color), (c) size (length and width), and (d) weight. Due to the importance of obtaining a consistent measure of product characteristics across farms with different crop cycles, BTDC staff phoned each farmer in advance to check the production stage and expected harvest day to schedule the followup survey right before or on the day of the harvest.

Upon arriving at the farm, surveyors directly sampled two dragon fruits from the farmer's field.[32] Sweetness was measured using a refractometer, which is a field device designed to measure soluble sugar content (degree brix) in fruits and vegetables. To account for sugar content variation across different parts of the fruit, surveyors collected measures at three different parts - top, middle, and bottom - of each fruit. I use the mean value as a measure of sweetness of the fruit. Appearance was rated on a 0-5 point scale on the fruit's skin and bract to assess whether visual defects, such as brown spots, were present. The length and width of the fruit were measured with a vernier caliper, and weight was measured using a portable scale. More details on the tools and ratings are presented in Appendix Section B.

The GAP audit module was an on-site audit of the farm conducted by BTDC staff to assess compliance with VietGAP standards taught in the training course. The auditor filled out a checklist with 32 items that could be marked as either pass or fail. While our checklist is a shorter version of the actual VietGAP checklist used to assess qualification for certification

[32] Farmers were compensated for sampling of fruits at a fixed rate of 15,000 VND per kilogram.

all 32 items in our checklist are compulsory items for VietGAP certification. The 32 items were chosen from the full 86-item list to represent the five management areas of GAP. For logistical and data quality reasons, farmers in the same strata were audited by the same auditor.[33]

To obtain a scientifically approved measure of farmer's compliance with GAP and proper use of pesticide, we conducted pesticide residue analysis through a private ISO-certified agricultural chemical testing laboratory in Ho Chi Minh city, Vietnam. Because of limited budgets, we were only able to conduct the pesticide analysis with three farmers from each cluster. Farmers were randomly chosen using a random number generator and contacted by BTDC staff in advance to schedule the sampling date which, in most cases, coincided with the date of the followup survey. Overall, a total of 264 farmers received the pesticide residue analysis.[34]

For the sampling procedure we hired specialists, who were not BTDC staff, trained for sampling agricultural products for pesticide analysis. The specialists followed the visit schedule arranged between BTDC staff and farmers without knowing each farm's treatment status. At each farm, specialists collected 4-6 kilograms of dragon fruit samples and packed them in sealed plastic bags to prevent the samples from being contaminated. BTDC prepared the plastic bags which were each labelled with a unique farmer ID. Once specialists came back to BTDC with the collected samples, BTDC staff recorded farmer IDs and packed the samples in carton boxes as preparation for shipment. We hired a logistics company for overnight shipping: the boxes were picked up at BTDC and delivered to the laboratory the next day.

Pesticide residue testing is a commonly practiced method by governments and agricultural businesses for testing compliance with food safety regulations, especially for imported fresh fruits and vegetables. A pesticide residue is the trace amount of any pesticide remaining on the treated product. Governments regulate pesticide residue in food products by setting

[33] In our main estimation, auditor-specific factors in audit scores are subsumed by strata fixed effects.

[34] We also sampled six farmers for pesticide residue testing from control communes outside the study area.

a Maximum Residue Limit (MRL), also known as food tolerance, which is the maximum concentration of a pesticide residue (expressed as mg/kg) that is legally tolerated in or on a food. MRLs are specific to a pesticide (or active ingredient in a pesticide) and crop type.

Each MRL is determined based on statistical analysis with a range of field trials in which pesticides are applied to crops according to GAP. That said, if a product's pesticide residue level exceeds the MRL it is a reasonably strong indicator of violation of GAP and food safety standards. In addition to the MRL being pesticide and crop specific, it also varies by country. Thus, we collected MRLs of the pesticides tested in this study for the following countries: European Union, United States, Japan, and China.[35]

4.5 Summary Statistics

Table 2 shows basic summary statistics from the baseline survey with farmers. Panel A shows demographics and farm characteristics. The average farmer has around 11 years of experience in growing dragon fruit and cultivates a dragon fruit farm with size of 0.75 hectares and around 750 dragon fruit trees. Forty percent of farmers reported to have received an agricultural certificate (e.g. VietGAP) prior to this study. More than half reported to have ever received a loan from a bank or borrowed money from other farmers for a farm-related expense. One-third of farmers reported to have saved at a formal bank before. In the past season (before training), the median farmer sold 6 tons of dragon fruit at an average price of 12,000 Vietnamese Dong (VND) per kilogram (which converts to approximately 0.5 U.S. Dollars). Across six different input expense categories, fertilizer had the highest expense (29 percent) followed by utilities (e.g. water and electricity) (27 percent).

Panel B presents summary statistics on farmer-intermediary trade characteristics. The information is based on farmer reports of sales to intermediaries in the season prior to the intervention. The median age of a farmer-intermediary relationship in which there was a

[35] These countries maintain online MRL databases from which MRL is available by crop and pesticide. For instance, Europe's MRL is available at the European Commission's online pesticide database: https://ec.europa.eu/food/plant/pesticides/eu-pesticides-database/public/?event=homepage&language=EN.

transaction in the previous season was 4 years. Only 1 percent of farmers had a formal written contract with an intermediary. In most transactions, the intermediary paid for harvesting costs (i.e. hiring laborers) and transportation of products from farm to facility. The vast majority of sales occur between farmers and local collectors (90 percent); only 6 percent are directly with an exporter and 3 percent are traded with a domestic retailer. Similar to customs export data 93 percent of products are exported to the Chinese market; 3 percent are exported to non-Chinese Asian markets; 1 percent of dragon fruit products are exported to E.U. and U.S. markets. Only 3 percent of products are for the domestic market.

Table 3 shows summary statistics on intermediary characteristics. The average age of an intermediary firm was about 9 years. In our intermediary sample, 54 percent are export enterprises, 45 percent are local collectors, and cooperatives consist the remaining 1 percent.[36] The average intermediary traded roughly 420 tons of dragon fruit during the past six months, or one season. This implies that an average intermediary trades with roughly 70 farmers with median sales volume in one season. The median intermediary purchased a kilogram of dragon fruit at 13,000 VND and sold it at 15,000 VND, leaving a margin of 2,000 VND. While most farmers reported to have no contracts with intermediaries, 41 percent of intermediaries reported to have a contract with their buyers. In terms of sales volume, 95 percent were sold as Chinese export, 3.5 percent as non-Chinese Asian export, and less than 1 percent were sold to either EU/US markets.

We conduct balance checks on farmer characteristics which are provided in Appendix Table A-2. Given the 4×2 factorial design of the experiment we test for differences between the seven treatment groups and the control group. We find very few statistical differences between treatment and control groups. Farmers in the intermediary training and certification treatment groups report slightly less experience in dragon fruit farming and grow fewer dragon fruit trees than farmers in the control group (column 7). Farmers in the farmer training and

[36]We classified intermediaries into export enterprise and local collector as follows: if an intermediary's main buyer is a foreign buyer then the intermediary is an export enterprise and if the main buyer is a local exporting company then the intermediary is a local collector. We separately asked if the firm is a cooperative.

certification treatment group show lower self-reported GAP compliance than that of control group farmers (column 6). Tests of joint significance of the seven treatment coefficients are all statistically insignificant except for expenses on hired labor (statistically significant at 5%). We include the baseline farmer characteristics as controls in the main regressions. The bottom two rows of Table A-2 report attrition in the first and second followup survey rounds. Attrition among farmers has been relatively low with only 2 percent not responding or refusing to take part in the first round and an additional 1 percent not participating in the second round. More importantly, the attrition rates of farmers do not vary across treatment and control groups.

Similarly, Appendix Table A-3 shows balance checks using intermediary characteristics. We find little evidence of statistical difference between treatment and control groups. Few exceptions include: intermediaries in farmer training and no certification treatment group has more experience with buyer (column 2); intermediaries in the no training and certification group export more to other Asian markets (column 5); and those in the intermediary training and certification treatment group self-report lower GAP compliance at their facility (column 7). The test of joint significance of all treatment groups shows that intermediary characteristics do not systematically vary with treatment status across groups. Moreover, attrition rates are neither shown to be significantly different between treatment and control groups. Note that intermediary's attrition rate (26 percent) was much higher than farmer's attrition rate (3 percent).

5 Empirical Results

This section presents experimental evidence on whether and how GAP training influences farmers' technology adoption, quality upgrading, and market performance as predicted by the theoretical model. For the main empirical specification and outcome variables we adhere to the empirical analysis outlined in the pre-analysis plan of this study registered at the

AEA RCT Registry. In case of using a specification or outcome variable not included in the pre-analysis plan we have stated this in the text for readers to take caution in interpreting the results.

5.1 Empirical Specification

Our main empirical specification includes a linear specification with indicators for each of the three training treatments as outlined in the pre-analysis plan. This specification allows us to separately estimate the effects of the three training treatments on farmer outcomes. Since the experiment is designed with two interventions we additionally include the certification treatment dummy along with interaction terms between each training group and certification treatment as controls.[37] This results in the following equation:

$$Y_{ics} = \alpha_0 + \Sigma_G \beta_G \text{Training}_{cs}^G + X_{ics} + \xi_s + \theta_t + \epsilon_{ics} \tag{7}$$

where Y_{ics} is the outcome of interest for individual i in farmer-intermediary cluster c and strata s, Training_{cs}^G is an indicator variable that takes the value one if cluster c is in training group $G = \{\text{Farmer, Intermediary, Joint}\}$, X_{ics} is a vector of farmer and intermediary characteristics at baseline, the certification treatment dummy and its interactions terms with the training treatment, ξ_s are strata fixed effects, θ_t is a fixed effect for survey round, and ϵ_{ics} is the idiosyncratic error term. Standard errors are clustered at the farmer-intermediary cluster level, which is our unit of randomization.

Our coefficients of interest are elements of vector $\beta_G = \{\beta_{Farmer}, \beta_{Intermediary}, \beta_{Joint}\}$ which measure different training treatment effects on production technology and product quality: $\beta_{\{Farmer\}}$ measures the impact of providing GAP training to farmers only, $\beta_{\{Intermediary\}}$ measures the impact of providing GAP training to intermediaries only, and $\beta_{\{Joint\}}$ measures the impact of providing GAP training to both farmers and intermediaries. Note that in joint

[37] In an experiment with multiple interventions, leaving out treatment interaction terms from the specification would bias the estimate of each treatment effect (Muralidharan, Romero, & Wuthrich, 2019).

training sessions farmers and intermediaries received training together — we did not provide training sessions separately to farmers and intermediaries.

The key identification assumption for causal interpretation of our coefficients is that farmers in treatment groups did not have systematically different outcomes from those in the control group for reasons other than the treatment itself. This assumption would be violated if, for instance, farmers self-selected into the GAP training program based on unobserved dimensions of farmers' abilities. Because treatments were randomized across groups within geographic strata, we believe that a farmer's treatment status is unrelated to the unobserved error term. Nonetheless, when interpreting the estimates we carefully consider possible side effects of the treatment that could potentially bias our results.

We estimate specification (7) using OLS estimation. In most parts of the analysis we pool the two survey rounds and estimate the average treatment effect across survey rounds. In case we believe that treatment effects are expected to evolve across rounds or if seasonal or temporal factors may largely influence the result we show the estimates separately for each round (reserved for the appendix section). For estimating the effect of training on sales outcomes we follow McKenzie (2012) and use the ANCOVA specification by including lagged outcomes from the baseline survey as controls.

In light of recent studies which document proper inference techniques with randomized experiments (e.g., see Young (2019)), we further conduct randomization inference tests and report p-values based on 5,000 permutations. The test is implemented by re-randomizing assignment of treatment separately for one of the training treatment without altering the other treatments within each strata. Specifically, since there are three training treatments in our study, one permutation involves three independent trials of randomization, once for each training treatment while holding the other two treatment assignments unchanged. The appeal of this test is that we can take advantage of our knowledge about the randomization process to avoid making distributional assumptions for inference. We acknowledge that this test was initially not included in the pre-analysis plan of this study.

Regarding concerns about statistical inference with multiple outcomes, we employ two approaches commonly adopted in the economics literature to address them. First, as in Kling, Liebman, and Katz (2007), when there are multiple outcome variables in the same evaluation group (e.g. product attribute is evaluated across six dimensions) we construct and test the aggregate index which is the average of the z-score across all outcomes. Each outcome's z-score is constructed by using the control group's mean and standard deviation. Second, as indicated in our pre-analysis plan, we follow Anderson (2008) and adopt the two-stage false discovery rate (FDR) control approach and report FDR-adjusted statistical significance levels indicated by stars next to the estimates.[38]

5.2 Effect of Training on GAP Technology Adoption

We start by estimating the effect of training on the knowledge and compliance of GAP, a measure of agricultural technology for producing high-quality food. The results are reported in Table 4. First, we find that training has a positive effect on farmers' knowledge about GAP. We tested farmer knowledge during the first follow-up survey round by asking 10 multiple choice questions based on the training material taught in the GAP training program. As reported in the first column, both farmer training and joint training increases farmers' GAP knowledge, by 0.32 and 0.29 standard deviations, respectively. However, intermediary training shows no increase in farmers' GAP knowledge. This potentially implies that farmers' knowledge increased through direct training but not indirectly through trained intermediaries. In contrast with the result on farmers' knowledge, none of the training treatments has a significant effect on farmers' awareness of food safety and pesticide use which was measured during the second round. This indicates that the training program increased knowledge without necessarily changing the level of awareness on food and pesticide safety issues which might have already been widespread among dragon fruit farmers.

Second, training also increases farmer's GAP compliance, as measured by records on farm

[38]Controlling the false discovery rate, or fraction of rejections which are type 1 errors, provides better power relative to controlling the familywise error rate (Anderson, 2008).

audit performance. Figure 3 provides visual evidence by showing the density distribution of standardized audit scores (measure of GAP compliance) by treatment group and survey round. Farmer training and joint training groups are shown to have distributions shifted to the right of the control group's distribution indicating higher technology adoption or compliance with GAP. In contrast, intermediary training group is similar or to the left of the control group's distribution.

We next estimate specification (7) using standardized audit scores on GAP compliance as a measure of technology adoption. Because the outcome is standardized using the control group's mean and standard deviation, the coefficient represents the difference in GAP compliance in the unit of the control group's standard deviation of GAP compliance. Column 3 presents the result with all 32 items on the audit list. It shows that training only farmers increases farmers' GAP compliance by approximately 0.42 standard deviations or 6.1 percent (0.42*0.1/0.72). Combining the results in columns 1 and 3 demonstrates that insufficient knowledge about technology could be a substantial barrier for technology adoption.

Interestingly, jointly training farmers and intermediaries shows an even stronger effect on GAP compliance which increases by 0.66 standard deviations or 9.2 percent (0.66*0.1/0.72). The test at the bottom of table 4 shows that the difference between the effect of farmer only training and joint training on GAP compliance is statistically significant (p-value = 0.04). This result is in sharp contrast to that for GAP knowledge as reported in Column 1, where we found no difference between these two training groups. Training has the same effect on farmers' knowledge, regardless of the presence of intermediaries while farmers have stronger incentives to put their knowledge into practice when there are intermediaries in the same group. One possible explanation in support for our asymmetric information argument is that simply acquiring knowledge does not directly transform to any benefit during sales transaction. Hence the interaction with buyers does not help. In contrast, the return of adopting GAP is higher in the joint training group where the information problems is reduced and improvement in quality through increasing GAP can better be sensed and valued by buyers.

Next, we evaluate treatment effects separately for each of the five areas of management practices of GAP. Dividing GAP compliance into five areas are informative for two reasons: first, it shows what area of practices are more likely to be adopted by trained farmers and second, it allows us to analyze in more detail how area-specific technology adoption relates to product quality (this result is shown later). To this purpose, we separately estimate specification (7) for each management category and report these estimates in columns 4-8. Farmer training has significant impacts on management of equipment (column 4), soil, water and waste (column 6), and pesticide (column 7). Joint training significantly improves all GAP categories except fertilizer management. When testing the difference in coefficients between the two training groups, audit scores on pesticide management is significantly higher for farmers in joint training than farmers in farmer only training.

In Appendix Table A-4, we report OLS estimates on GAP compliance by each survey round to examine temporal patterns in technology adoption behavior. The results between the two panels are both quantitatively and qualitatively similar. This indicates that the impact of training observed at six months after training lasted for at least another six months until our second follow-up survey. The lasting impact of training on farmer's management practices and GAP compliance is not unreasonable since some practices are irreversible (e.g. purchase of equipment and setting up signs indicating area of chemical spray). However, certain measures of GAP compliance also require constant monitoring and input of resources after the initial implementation (e.g. record keeping of the production process, tracking pesticide use, and maintaining hygiene and safety in the production area).[39] Therefore, the consistency in findings across the two tables can be partially attributable to changes in farmers' daily farm management practices.

[39]To pass audit items related to record keeping or tracking substance use, it was mandatory for farmers to present log books to auditors. In other words, if farmers could not provide hard evidence of book keeping the item was marked as fail.

5.3 Effect of Training on Quality Upgrading

GAP compliance provides a measure of how well a farmer implemented a set of farm management practices that are designed to improve food safety and reduce improper pesticide use. In the previous section, we report evidence on the effectiveness of training on technology adoption (i.e. GAP compliance). In this section we further test whether the training intervention and technology adoption led to meaningful improvements in product quality. The quality measure is based on laboratory tests of 18 pesticide residues with 264 randomly sampled farmers. In Appendix Table C-1, we present the list of 18 pesticides along with its Hazard Classification (WHO, 2010) and MRLs set by E.U., U.S., Japan, and China.

Table 5 presents a summary of pesticide residue levels found in our dragon fruit samples. Among the 18 pesticides, 7 pesticides had residue levels above the limit of detection (LOD) in at least one farmer sample.[40] Based on EU's MRL regulation, the three most common pesticides with residue levels exceeding its MRL are Permethrin (22 percent of samples), Dithiocarbamates (57 percent of samples), and Carbendazim (44 percent of samples).[41] Importantly, Carbendazim is not permitted for use in agriculture in Vietnam.In terms of the sum of incidences exceeding MRL, the average sample contained more than one type of pesticide violating the maximum residue limit set by E.U. countries or U.S and 78 percent of samples had at least one type of pesticide with residue above the MRL. In contrast, if we adopt China's MRL as the safety standard, only 0.13 pesticides are found to violate its MRL in the average sample and about 12 percent of samples contained at least one type of pesticide exceeding the maximum limit. This comparison clearly shows that China's regulation on pesticide use in agricultural products is indeed less strict than that adopted in E.U. countries and the U.S.

Table 6 explores whether GAP training had meaningful impacts on pesticide residue

[40]Limit of detection is defined as the lowest quantity or concentration of a substance that can be detected with a given analytical method.

[41]Permethrin is an insecticide effective against a wide range of insects and pests, but known to be lethal to honey bees. Dithiocarbamates is used as a fungicide with extensive application on fruit crops. Carbendazim is a fungicide used for controlling plant diseases in cereals and fruits.

levels. Columns 1-4 use as outcome variable the incidence of residue exceeding the MRL of each of the four countries. Columns 2 and 3 show that joint training reduces the incidence of pesticide residue violating U.S's MRL 31 percent (0.37/1.21) and Japan's MRL by 70 percent (0.43/0.61), respectively. We also see a 21 percent (0.31/1.48) decline in pesticide residue violation under E.U.'s MRL yet the coefficient is not statistically significant. While the coefficients for farmer training are also negative the magnitudes are only half of that of joint training and statistically insignificant. In column 4, we find zero treatment effect when incidence of violation is measured using China's MRL.

Columns 5-8 use mean residue amount, scaled at each country's MRL, as the outcome variable. Here we find that both farmer only training and joint training led to significant reductions in the amount of pesticide residue found in dragon fruit samples. Column 5 suggests that farmer training and joint training reduces pesticide residue in units scaled at E.U.'s MRL by 33 percent (0.46/1.40) and 50 percent (0.71/1.40), respectively. While it is possible for farmers to reduce pesticide residue through other farming practices and not necessarily through applying GAP the results in Tables 4 and 6 jointly suggest that implementation of GAP and improvements to pesticide management lowered pesticide residue levels and raised compliance with the MRL set by different countries.

While GAP is primarily designed to raise food safety and regulate pesticide use its implementation may have had unintended consequences on product characteristics, such as sweetness or appearance, which may be important factors of customer demand and affect farm price and sales accordingly. Therefore, we next examine whether GAP training affected product attributes which are typically valued on the market. We drew on consultations with farmers, intermediaries, and BTDC experts and chose four dimensions of product characteristics valued in the market for dragon fruit: (1) sweetness, (2) appearance, (3) size, and (4) weight.

Table 7 presents OLS estimates of training effects on product attributes using specification (7). Each column is a separate regression with a different measure of product characteristic standardized by the control group's mean and standard deviation. Because there are six measures of product quality to account for multiple hypothesis testing we calculate the average z-score across six attributes as an index of overall product attribute (Column 7). One potential concern is that, unlike testing in a laboratory environment, product attributes were measured in the field in relatively small samples making it prone to measurement errors and attenuation bias. Thus, we would like to emphasize that the results on product attributes are to be interpreted with caution. That said, across all seven columns we find no significant difference in product attributes between treatment groups and the control group.

Table 8 shows relationships between GAP compliance by management category and product quality outcomes. We regress each measure of quality (pesticide residue under EU standards and product attributes) on the standardized scores of five management areas and report the estimated coefficients under each column. The results in the first two columns support the view that adopting GAP's pesticide management is likely to improve food quality and comply with E.U.'s food safety standard. Higher compliances to hygiene and safety management and soil, water, and waste management are also associated with lower pesticide residue levels (although the estimate size is only one-fifth of that associated with pesticide management). Other management categories do not show a significant relationship with reducing pesticide residue levels. Of course, these relationships may not be entirely causal. Yet the results provide some degree of understanding on which management areas of GAP may be more relevant to increasing food safety and product quality.

Overall, the empirical evidence provided so far are consistent with our theoretical predictions: predictions 1 and 2. Training equips farmers with knowledge which in turn lowers their marginal cost of quality upgrading leading to production of higher quality fruits as measured by lower pesticide residue. In addition, joint training facilitates relationship building between farmers and intermediaries and reduces information frictions in the supply chain, generating greater incentives for farmers to improve product quality.

5.4 Effect of Training on Export, Revenue, and Inputs

Given the positive effect of training on farmers' technology adoption and quality upgrading, one natural question to ask is: do farmers benefit from such improvements in farm technology and product quality? This question is important because it can help us understand whether the farmers have economic incentives to invest in quality upgrading technology. Accordingly, in this section, we examine whether the training has a positive effect on farmers' market performance, in terms of export, sales, and input costs. As a measure of market performance we utilize farm-intermediary trade information reported by farmers during follow-up surveys and conduct a series of empirical analyses using this data.

Table 9 reports treatment effects on export market performance using farmer-intrermediary trade data pooled across the two survey rounds. We categorize markets into four destination groups: Domestic, China, Asia (excluding China), and EU/US (includes all non-Asian countries). In columns 1-4, the outcome variable is an indicator variable with value one if a farmer reported a positive sales volume to the market and zero otherwise. In columns 5-8, the outcome variable is the log of sales volumes to each market. We find that joint training significantly increases sales to other Asian markets (19.4 percentage point rise in percentage of farmers selling to Asian markets and 167 percent increase in export volume). Most surprisingly, we find no similar effect of farmer training on export market performance. We also find no effect of intermediary training on export market performance. Column 9 suggests that none of the training treatments had a statistically significant effect on total sales volume. Compared with the farmer training group, the joint training group shows lower incidence and amount of export to China and higher export volume to other Asian countries. As there is no significant changes in the total volume, these results plausibly suggest that GAP training and quality upgrading induced export reallocation from Chinese market to other proximate markets with higher markup.

While it is possible for farmers to explore more profitable high-markup markets through channels other than improvement in GAP compliance, Table 10 provides further evidence on the reason of market switch. It reports the marginal effect of different attributes on market destination. One standard deviation improvement in GAP compliance increases the probability of exporting to EU/US by 1.1 percent and to other Asian markets by 4.7 percent. It also decreases the probability of selling to domestic market by 0.6 percent and Chinese market by 5.1 percent. Tables 9 and 10 together imply that technology adoption and quality upgrading are most likely associated with switching from the Chinese market to other Asian markets.

Table 11 reports results on various components of farm business: price sold at the farm gate, revenue, total cost, seasonal profit, and annual profit. Price is derived as the average of prices sold to intermediaries in each survey round. We construct two measures of revenue using farmer reports in surveys. The first measure directly asks farmers to report their farm revenue in the current season. The second measure constructs revenue from the farmer-intermediary trade survey which contains detailed information on price and volume of each sale. Similarly, we construct two measures of profit by subtracting total input cost from the first and second measures of revenue respectively. We believe that the first profit measure closely corresponds to the profit measure recommended by de Mel, McKenzie, and Woodruff (2009) because in our context revenues and expenses are both aggregated at a well-defined seasonal production level.[42] Total cost is calculated by adding farm expenses across six specific input categories plus an additional unspecified category.[43] All variables are log-transformed to ease the interpretation of the coefficients.[44]

Results show that on average farmers in the joint training group received 10.3 percent higher price and earned significantly higher revenue, implied by the farmer-intermediary trade data. Farmers in the joint training group also spent significantly more on production

[42] de Mel et al. (2009) recommends using a direct report on profit as a measure of eliciting profits from small firms than constructing it from reported revenue minus reported expenses because calculated profit can often involve a mismatch of timing between expenses and revenues.

[43] In the unspecified category, farmers could report any expenses on inputs that does not fall into one of the six categories. Results are robust to dropping expenses in the unspecified category.

[44] Derived profits were negative for some farmers. Accordingly, for conversion to log-scale, we adjust profits by subtracting each farmer's profit with the profit at the bottom 10th percentile.

inputs than control group farmers. In contrast, farmers in the farmer training group show no significant change in their prices, revenues or production input costs. Seasonal profit is roughly 10 percent higher yet statistically insignificant among farmers in joint training. Annual profit aggregates revenue and cost across the two seasons and is shown to be almost 20 percent higher (lacks precision for statistical significance) for the joint training group compared to the control group. Although we fail to reject the null hypothesis of profit in the joint training group being higher than the control group, when compared with the farmer training group, we do reject equivalence of profits between farmer training and joint training at conventional levels of statistical significance. We believe this is because farmer training had also raised input costs of farmers and led to slightly negative profits.

There are many possible explanations for the increase in price in the joint training group. For example, the price return is higher for given quality; quality premium is fixed but farmers increase quality within a given destination market. Table 12 presents quality premium for different attributes in each market destination destination and sheds light on the mechanism of price increase. There is positive returns to GAP compliance or higher quality, but the variation in prices is fully absorbed by different market destination and no longer relates to quality aspects. In other words, conditional on entering a specific market, there is no return to quality upgrading. Figure 4 further shows quality premium in each market by different treatment group. We find that there is a positive price premium for GAP compliance in the joint training group when exported to Asian or EU/US markets. However, it is not significantly different from other groups where quality is expected to be not rewarded. These two pieces of evidence together suggest that quality premium for a given market is rather stable during our intervention. Therefore, rather than systematical increase in returns to quality, the higher prices that joint training farmers receive may be mainly attributed to market switch from lower-priced Chinese market to other Asian countries.

Table 13 presents estimates on treatment effects on farm input expenses. Input expenses are broadly categorized into six groups: fertilizer (column 1), pesticide (column 2), facility (column 3), equipment (column 4), hired labor (column 5), and utility (column 6). Column 7 represents the sum of input expenses, excluding farmer's own work hours (column 8). For technology adoption (i.e. comply with GAP), farmers may need to purchase new equipment and build facilities for storing tools, fertilizers and pesticides. In addition, farmers may be induced to purchase authentic, high-quality fertilizers and pesticides to comply with proper pesticide management practices.

In the joint training group, we find significant increases in spending on pesticide (30 percent), facility (95 percent), and utility (22 percent). In the farmer training group, we also see significantly higher spending on facility (54 percent) but not in pesticide spending. Overall, total input expenditure increases about 16 percent in the joint training group and 12 percent in the farmer only training group. Column 8 shows the result with farmer's own work hours, measured as farmer's average daily work hours. We do not observe any significant increase in work hours among treatment group farmers.

To examine the evolution of input expenses over the course of an year, Appendix Table A-5 reports estimates on input expenses by each survey round. The results suggest that spending on facility mostly occurs during the first six months after training. This finding can be consistent with an initial upgrading of farm facilities to comply with GAP standards. However, spending on pesticides is consistently high for joint training group farmers throughout the twelve months after training. This may be because pesticide expenses are incurred every season and if GAP training induced farmers to use high-quality pesticides which comes at a higher cost then pesticide expenditure can be expected to be higher every season.

5.5 Discussion

The experimental findings above demonstrate the effects of training on farmer's technology adoption, quality provision and market performance. Our theoretical framework predicts that training improves farmers' production efficiency and consequently farmers upgrade product quality. The results from our randomized experiment confirms this prediction: Farmers increase GAP compliance by 0.4 - 0.7 standard deviations and improve quality provision in terms of reducing pesticide residue by 50 percent. While farm-gate price increases about 10 percent there is no significant changes in revenue and profitability. Farmers also spend more on production inputs.

Qualitatively, these results are consistent with findings in the agricultural technology adoption literature (Cole and Fernando (2020) on cotton cultivation practice, Grimm and Luck (2020) on organic farming, Larsen and Lilleør (2014) and Y. Pan, Smith, and Sulaiman (2018) on food security and D. Pan, Kong, Zhang, and Ying (2017) on fertilizer usage). To put the size of effects into perspective, Cole and Fernando (2020) find that providing mobile advice increases farmers' adoption by 0.1-0.2 standard deviation and the input cost rises by about 8 percent. Kondylis et al. (2017) show that training leads to a 20 percent increase in the adoption of sustainable land management (SLM) and Hörner, Bouguen, Frölich, and Wollni (2019) finds an 11 percent increase in integrated soil fertility management.

We also show that the impacts of training vary across different training treatment groups. With the presence of intermediaries in the same training group, training is more effective in increasing technology adoption, especially in pesticide management. While the difference may not be statistically significant, the estimate for joint training for pesticide residue, our main quality measure, is roughly twice the magnitude of the estimate for farmer only training.

Another interesting finding is that the impact of training on export performance differs significantly for farmer only and joint training groups. Trading volume flows out from Chinese market and into other Asian countries in the joint training group but we observe no such pattern in the farmer training group. This coincides with the finding that farmers in the joint training group also receive higher price than farmers in the farmer training group.

5.5.1 Was training effective in increasing intermediary's knowledge?

We find no impact of intermediary training on farmers' knowledge, technology adoption, and quality upgrading. This is possible if intermediaries had not actually learned from the training program such that there is no change in intermediary's knowledge after treatment. In Table 14, we directly test this possibility by examining whether training increased intermediary's knowledge.[45] Column 1 suggests that intermediary training and joint training improved intermediary's knowledge on GAP by 0.4 and 0.5 standard deviations, respectively. Note, however, that the randomization inference test indicates that only joint training is statistically significant at the 1 percent level; the randomization inference p-value for intermediary training is 0.132. Farmer training has no impact on intermediary's GAP knowledge. Therefore, the results in column 1 rule out lack of intermediary knowledge on GAP as an explanation for why we see no effect of intermediary training on farmers' technology adoption. This also arguably implies that the large effect from joint training is not driven by intermediary's knowledge transfer on GAP technology to farmers but rather driven by mitigating asymmetric information or by building reliable relationships between farmers and intermediaries.

Next, we use audit reports on intermediaries packing facilities to examine whether training induced intermediaries to upgrade their packing facilities according to GAP standards (e.g. cold-chain system, sanitizing equipment, hygiene and safety). Column 2 shows that compared to the control group none of the training groups show significantly higher facility quality, measured by audit scores on GAP compliance. Combining this with the previous result suggests that while training intermediaries increased their knowledge it neither diffused to farmers along the supply chain nor had the change in knowledge induced intermediaries to improve the quality of their facilities. Additionally, as shown in columns 3-8 of Table 14 and columns 1-8 of Table 15, we find no training effect on intermediary's business outcomes — farm-gate price, facility-gate price, sales volume, revenue, cost, and profits. We admit that the sample size of intermediaries that participated in the follow-up surveys is small and the results shown here may suffer from low statistical power.

[45] Other possible reasons for no knowledge transfers in our context are 1) intermediaries were reluctant to train farmers because of weak contracting environment, 2) cost of training makes it unprofitable for intermediaries to do so, or 3) farmers are reluctant to learn from intermediaries because intermediaries are not perceived to know better about production technology than themselves.

5.5.2 Did GAP training spillover to farmers in the control group?

Finally, at the stage of designing this experiment we were concerned about spillovers across treatment groups within the treated regions. To address this issue we sampled four farmer groups within the same province but from outside the two districts in which we ran the training programs and designated them as spillover-proof control groups.[46] These spillover-proof control groups were located sufficiently far away from any treated farmer group and we believed that the probability of knowledge spillovers from treated groups in treated regions to these farmer groups in untreated regions is extremely low. As we did with the control groups in treated regions, we provided no training to these groups but conducted all three surveys.

Our method for examining spillovers is to test differences in the main outcome variables between control farmers in treated districts and control farmers in untreated districts (spillover-proof control group). As we compare across districts we leave out the strata fixed effects from the specification. The results are presented in Appendix Table A-6. The first column shows the mean of outcome variables of farmers in untreated districts. The coefficient estimate of difference between the two control groups is shown in the second column followed by the standard error and p-value.

Panel A test differences in baseline characteristics and shows that control farmers in treated districts have slightly fewer dragon fruit trees and higher farm-gate price than farmers in untreated districts. In Panel B, we find that control farmers in treated districts have higher GAP compliance than those in untreated districts implying that farmers in treated districts have higher rate of technology adoption than farmers in untreated districts even without receiving training. However, despite higher GAP compliance, farmers in treated districts do not seem to have significantly better product quality—pesticide residue and product attribute.[47] Panel C indicates that farmers in treated districts are less likely to export to

[46] The sampling of spillover-proof groups as to serve as another control group is included in the pre-analysis plan of this study.

[47] When we test differences separately for each of the five areas of GAP management, we find treated district farmers to have higher compliance than farmers in untreated districts in equipment management and fertilizer management but no difference is found in pesticide management.

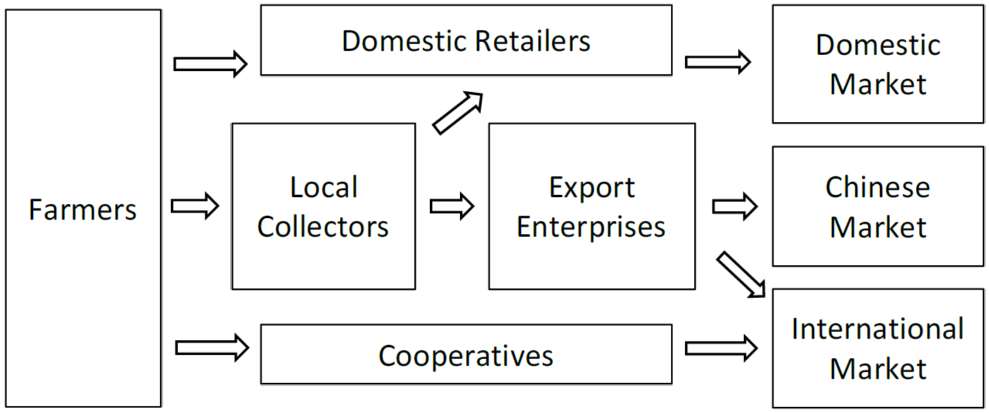
China (but not more likely to export to other Asian countries) and spend more on inputs.[48] Overall, we find some evidence of technology spillover in treated districts. Nonetheless, we do not observe increases in product quality nor market performance among control farmers in treated districts.

6 Conclusion

This paper empirically examines how a supply side constraint — lack of technology to produce quality – and a demand side constraint — asymmetric information between intermediaries and farmers — hinder technology adoption and quality upgrading in the context of an agricultural supply chain. We first present a theoretical framework to draw predictions on the effects on relaxing these two constraints. Then we test these predictions in the context of Vietnam's dragon fruit supply chain by examining the impact of a randomized training intervention that was implemented across two major districts. The intervention provided training to farmers and intermediaries, intended to lever up producers' production efficiency, and also an opportunity for farmers and intermediaries to build relationships through joint training sessions. We show that the training intervention raised technology adoption and quality provision. Farmers who were jointly trained with intermediaries were more likely to sell their products to high-price export markets and earn higher revenue. The results are consistent with a theoretical model emphasizing endogenous quality provision in the presence of heterogeneous productivity and asymmetric information on quality between farmers and intermediaries.

[48] The difference in average farm-gate price is also observed in the baseline characteristics.

Figure 1: Dragon Fruit Supply Chain of Binh Thuan province



Notes: This figure illustrates the dragon fruit supply chain in Binh Thuan Province.

Figure 2: Timeline and Interventions

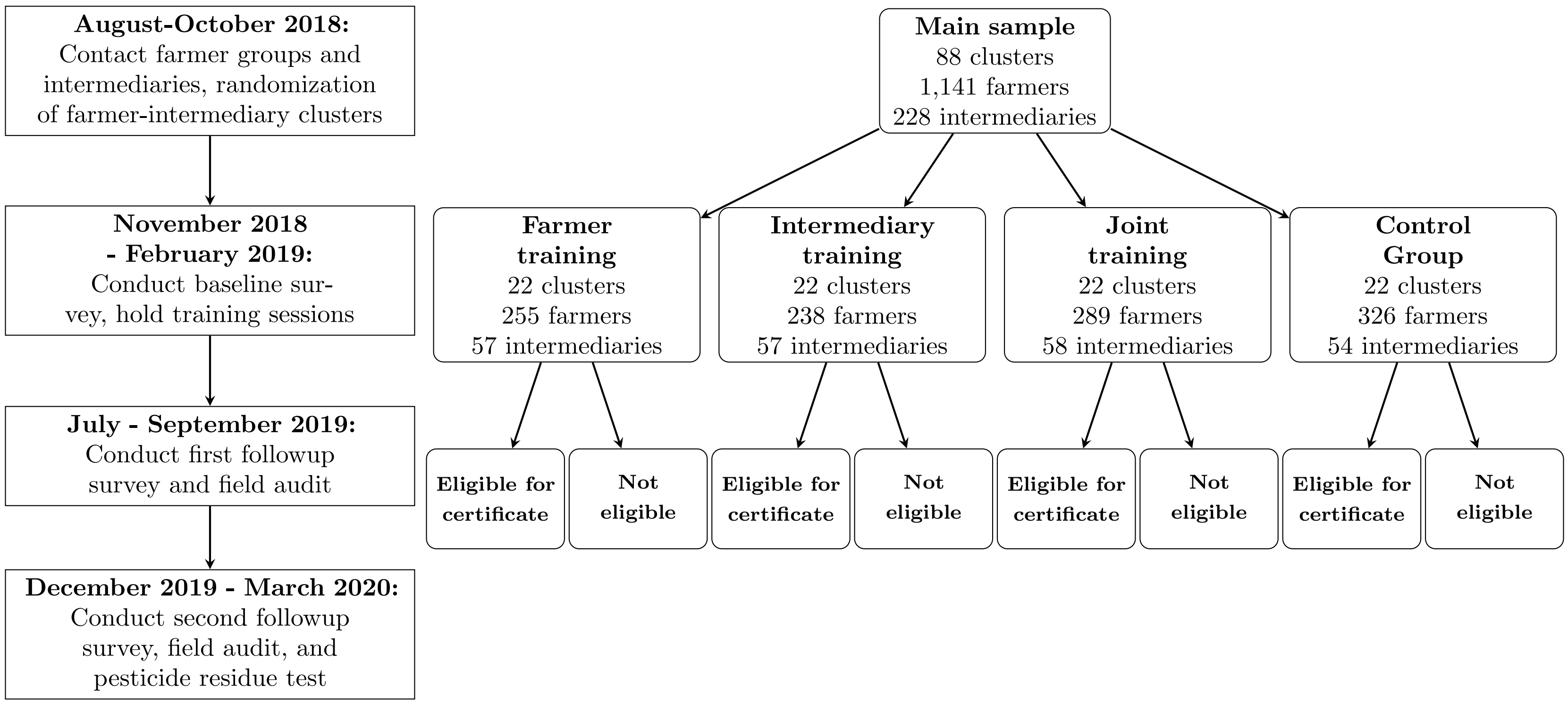
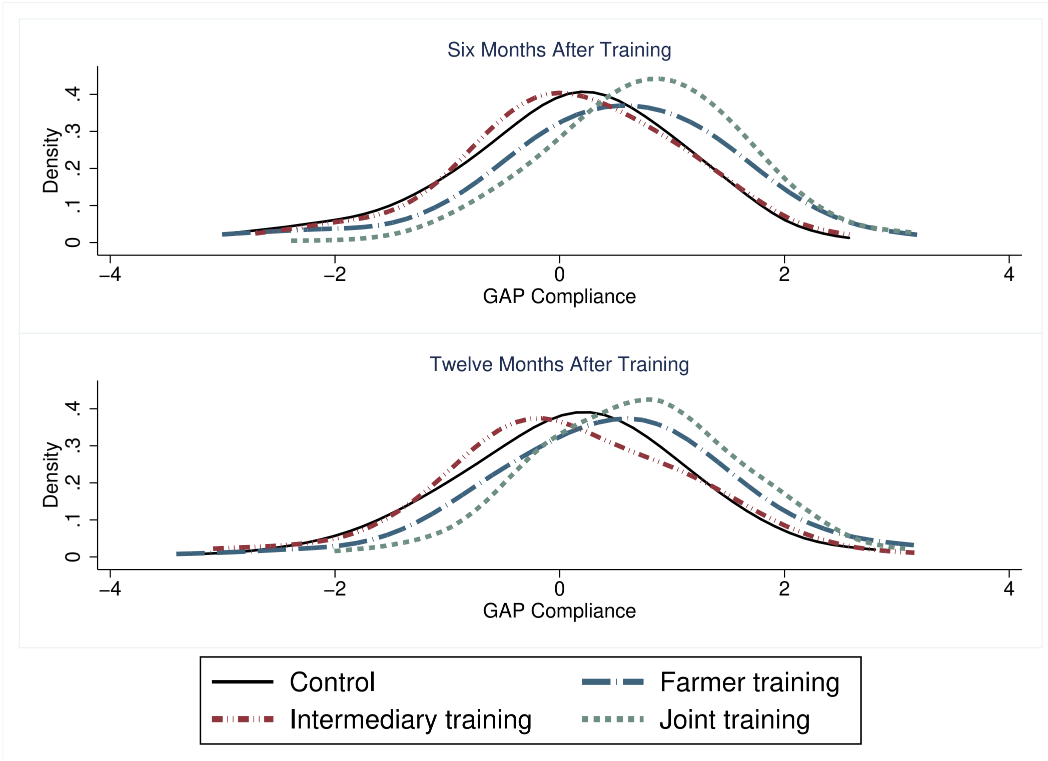
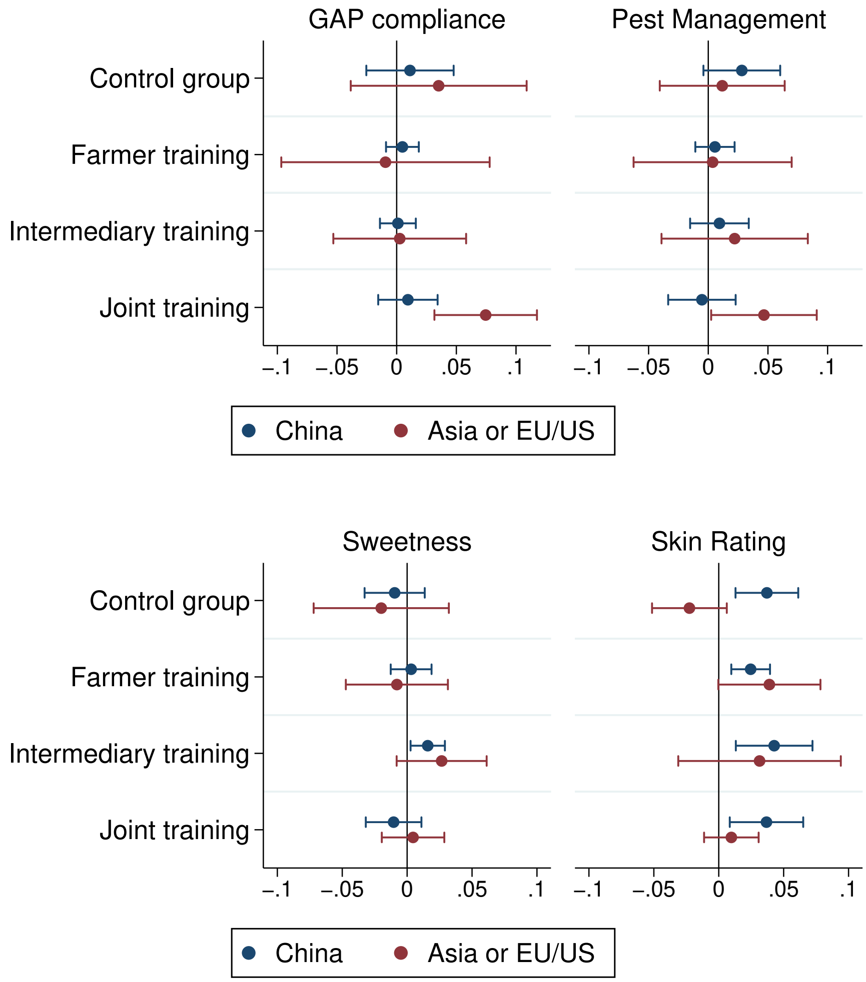


Figure 3: Density Distribution of GAP Compliance by Training Treatment



Notes: This figure shows distribution of standardized audit scores from first (top panel) and second (bottom panel) rounds of follow-up survey.

Figure 4: Price Premium for Quality by Export Market



Notes: This figure plots estimates on interaction terms (training treatment × standardized product quality) with specific market's farm-gate price as the dependent variable. Data on farm-gate price and product quality are from two follow-up survey rounds. GAP compliance is total score on GAP audit; Pest Management is score on pesticide management; Sweetness and Skin Rating are measures from the product assessment module. A positive coefficient estimate indicates that farm-gate price is increasing in product quality when sold to respective market.

Table 1: Vietnamese Dragon Fruit Exports by Country in 2015 and 2019

Country	2015 Volume (1,000 ton)	2015 Value (1M USD)	2015 Unit Price (USD)	2019 Volume (1,000 ton)	2019 Value (1M USD)	2019 Unit Price (USD)
China	579.2	417.9	0.72	1878.5	1131.1	0.60
Hong Kong	18.5	11.5	0.62	11.6	8.4	0.72
Thailand	12.9	7.0	0.54	6.8	4.9	0.72
Japan	3.2	2.3	0.72	0.2	0.6	3.00
Singapore	1.7	1.2	0.71	1.2	0.7	0.58
India	1.5	1.2	0.80	1.8	1.4	0.78
Netherlands	1.0	2.2	2.20	1.0	4.1	4.10
United States	0.9	6.1	6.78	1.0	4.1	4.10
Canada	0.4	0.4	1.00	0.6	1.1	1.83
South Korea	0.3	0.7	2.33	0.7	1.7	2.43

Source: Data provided by General Department of Vietnam Customs. The table shows top 10 countries in terms of Vietnamese dragon fruit export volume.

Table 2: Summary Statistics of Farmer Characteristics at Baseline

	Obs.	Mean	Median	S.D.	Min	Max
Panel A. Demographics and Farm Characteristics						
Age	1141	45.59	45.00	12.58	18	88
Female	1141	0.34	0.00	0.47	0	1
Secondary Education	1141	0.70	1.00	0.46	0	1
Experience growing dragon fruit (years)	1141	10.69	10.00	6.07	0	40
Size of dragon fruit farm (hectares)	1141	0.75	0.50	0.73	0	10
Number of dragon fruit trees	1141	764.88	600.00	705.47	100	10000
Received any agricultural certificate before	1141	0.42	0.00	0.49	0	1
Ever received loan for farm investment	1141	0.62	1.00	0.48	0	1
Ever saved at bank	1141	0.35	0.00	0.48	0	1
Raven matrices score	1141	4.27	3.00	3.53	0	12
Time discounting - present biased	1141	0.24	0.00	0.43	0	1
Self-reported GAP compliance	1141	0.60	0.57	0.20	0	1
Volume sold (tons)	1141	10.05	6.00	12.19	0	120
Average price (1,000 VND/kg)	1141	12.69	12.00	3.53	2	25
Farm work hours	1141	6.54	6.00	1.84	0	14
Expenses on Fertilizer (1 Million VND)	1141	28.72	15.00	50.27	0	1000
Expenses on Pesticide (1 Million VND)	1141	2.42	0.00	6.28	0	70
Expenses on Facility (1 Million VND)	1141	1.75	0.00	23.16	0	720
Expenses on Equipment (1 Million VND)	1141	4.28	0.00	12.46	0	175
Expenses on Paid Labor (1 Million VND)	1141	9.73	2.00	19.96	0	220
Expenses on Utility (1 Million VND)	1141	26.70	10.00	101.39	0	3000
Total Expenses on Inputs (1 Million VND)	1141	74.56	39.00	154.87	0	4046
Panel B. Farmer-Intermediary Trade Characteristics						
Experience trading with intermediary (years)	1883	4.88	4.00	3.46	0	22
Trade based on formal written contract	1883	0.01	0.00	0.10	0	1
Intermediary paid for harvesting cost	1883	0.91	1.00	0.29	0	1
Intermediary paid for transportation cost	1883	0.98	1.00	0.12	0	1
Intermediary is collector	1883	0.90	1.00	0.29	0	1
Intermediary is exporter	1883	0.06	0.00	0.24	0	1
Intermediary is domestic retailer	1883	0.03	0.00	0.17	0	1
Product for Chinese market	1876	0.93	1.00	0.25	0	1
Product for Asian (excluding China) market	1876	0.03	0.00	0.16	0	1
Product for EU/US market	1876	0.01	0.00	0.11	0	1
Product for Domestic market	1876	0.03	0.00	0.17	0	1

Notes: This table provides summary statistics on farmer demographics, farm characteristics, and farmer-intermediary trade reported by farmers collected from baseline survey. The unit of observation in panel B is farmer-intermediary trade pair.

Table 3: Summary Statistics of Intermediary Characteristics at Baseline

	Obs.	Mean	Median	S.D.	Min	Max
Years of intermediation business	228	9.31	8.00	5.26	1	24
Type = collector	228	0.45	0.00	0.50	0	1
Type = export enterprise	228	0.54	1.00	0.50	0	1
Type = cooperative	228	0.01	0.00	0.11	0	1
Size of packing/collection facility (m^2)	228	1176.05	800.00	1148.89	50	7000
Trade volume (tons)	228	422.32	320.00	318.84	50	2000
Average purchase price (1,000 VND/kg)	228	15.26	15.00	2.33	10	22
Average sales price (1,000 VND/kg)	228	17.62	17.00	2.79	11	26
Self-reported GAP compliance	228	3.50	4.00	1.28	0	6
Contract with buyer	228	0.41	0.00	0.48	0	1
Years of experience with buyer	228	5.40	5.00	3.13	1	20
Volume of Chinese exports (tons)	228	316.73	240.00	232.93	0	1800
Volume of Asian exports (tons)	228	11.71	0.00	41.65	0	367
Volume of EU/US exports (tons)	228	0.53	0.00	6.75	0	100
Volume of domestic sales (tons)	228	3.70	0.00	13.74	0	100
Expenses on labor (1M VND)	228	439.82	355.00	342.92	0	1800
Expenses on utility (1M VND)	228	280.08	142.50	403.47	0	3000
Expenses on materials (1M VND)	228	491.95	200.00	740.48	0	5000

Notes: This table provides summary statistics on intermediary characteristics collected from baseline survey.

Table 4: Treatment Effects on Farmer's Knowledge, Awareness, and Compliance

	Self report		Audit report on Compliance					
	Knowledge (1)	Awareness (2)	Total (3)	Equipment (4)	Hygiene (5)	Soil (6)	Pesticide (7)	Fertilizer (8)
Farmer Training	0.320**	0.137	0.424***	0.327***	0.142	0.312***	0.312***	-0.095
	(0.092)	(0.115)	(0.091)	(0.099)	(0.088)	(0.092)	(0.076)	(0.088)
	[0.011]	[0.412]	[0.002]	[0.042]	[0.181]	[0.046]	[0.004]	[0.428]
Intermediary Training	0.024	-0.051	0.112	0.100	0.026	0.171	0.071	-0.197*
	(0.093)	(0.085)	(0.101)	(0.107)	(0.096)	(0.111)	(0.077)	(0.107)
	[0.834]	[0.202]	[0.221]	[0.204]	[0.296]	[0.245]	[0.382]	[0.181]
Joint Training	0.291***	0.177	0.660***	0.450***	0.216**	0.402***	0.549***	0.042
	(0.081)	(0.112)	(0.109)	(0.099)	(0.087)	(0.118)	(0.078)	(0.085)
	[0.008]	[0.064]	[0.000]	[0.001]	[0.001]	[0.010]	[0.001]	[0.206]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.73	0.74	0.04	0.27	0.40	0.44	0.00	0.03
Control mean (Pass/Total)	5.83	3.75	0.72	0.61	0.81	0.72	0.71	0.90
R-squared	0.19	0.30	0.17	0.14	0.14	0.09	0.11	0.05
Observations	1107	1092	2201	2201	2201	2201	2201	2201

Notes: This table reports treatment effects on farmer's GAP knowledge, awareness of pesticide use, and GAP compliance. The results use data from two follow-up survey rounds. Dependent variables are standardized by the control group's mean and standard deviation. Column 1 measures farmer's knowledge on GAP based on a test consisting of 10 multiple choice questions conducted during first follow-up survey round. Column 2 measures farmer's awareness using self-reports on pesticide use and safety in second follow-up survey found (higher score indicates farmer has greater awareness on health safety issues with pesticide use). Column 3 uses total audit score which is the number of items passed across all 32 items. Columns 2-5 use number of items passed in each management category. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 5: Summary of Pesticide Residue Levels in Dragon Fruit Samples

Pesticide (A.I.)	Obs.	Mean (mg/kg)	S.D.	Pr($\text{Residue}_\rho > \text{MRL}_\rho$) E.U.	U.S.	Japan	China
Chlorpyrifos	264	0.000	0.000	0.00	0.00	0.00	0.00
Difenoconazole	264	0.003	0.019	0.01	0.00	0.02	0.02
Fipronil	264	0.000	0.000	0.00	0.00	0.00	0.00
Metalaxyl	264	0.000	0.004	0.00	0.00	0.00	0.00
Permethrin	264	0.039	0.090	0.22	0.00	0.00	0.00
Phenthoate	264	0.000	0.000	0.00	0.00	0.00	0.00
Prochloraz	264	0.000	0.000	0.00	0.00	0.00	0.00
Quinalphos	264	0.000	0.000	0.00	0.00	0.00	0.00
Tebuconazole	264	0.000	0.000	0.00	0.00	0.00	0.00
Hexaconazole	264	0.009	0.040	0.06	0.06	0.02	0.05
Thiabendazole	264	0.000	0.000	0.00	0.00	0.00	0.00
Azoxystrobin	264	0.000	0.000	0.00	0.00	0.00	0.00
Chlorothalonil	264	0.000	0.000	0.00	0.00	0.00	0.00
Acetamiprid	264	0.000	0.002	0.01	0.00	0.00	0.00
Cyprodinil	264	0.000	0.000	0.00	0.00	0.00	0.00
Dithiocarbamates	264	0.183	0.247	0.57	0.57	0.06	0.00
Pyraclostrobin	264	0.000	0.000	0.00	0.00	0.00	0.00
Carbendazim	264	0.141	0.186	0.44	0.45	0.31	0.06
Σ_ρ Pr($\text{Residue}_\rho > \text{MRL}_\rho$)	264			1.31	1.08	0.42	0.13
Pr (Σ_ρ Pr($\text{Residue}_\rho > \text{MRL}_\rho$) > 0)	264			0.78	0.73	0.35	0.12

Notes: This table provides summary statistics on pesticide residue levels in dragon fruit samples tested for this study.

Table 6: Treatment Effects on Pesticide Residue

	Σ Pr(Residue$_\rho$ > MRL$_\rho$)				Mean Residue Amount (unit: $\times$ MRL)			
	E.U.	U.S.	Japan	China	E.U.	U.S.	Japan	China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmer Training	-0.211	-0.178	-0.249	0.100	-0.459*	-2.761**	-0.057	0.012
	(0.164)	(0.158)	(0.154)	(0.108)	(0.267)	(1.343)	(0.045)	(0.039)
	[0.187]	[0.214]	[0.192]	[0.522]	[0.084]	[0.074]	[0.294]	[0.784]
Intermediary Training	0.075	0.042	0.059	0.090	-0.099	0.571	0.040	-0.004
	(0.201)	(0.184)	(0.128)	(0.088)	(0.293)	(1.390)	(0.039)	(0.034)
	[0.810]	[0.804]	[0.742]	[0.128]	[0.746]	[0.642]	[0.260]	[0.871]
Joint Training	-0.309	-0.367*	-0.428***	-0.049	-0.707**	-3.976***	-0.106**	-0.042
	(0.173)	(0.153)	(0.131)	(0.088)	(0.242)	(1.230)	(0.036)	(0.029)
	[0.010]	[0.001]	[0.001]	[0.547]	[0.002]	[0.001]	[0.001]	[0.060]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.49	0.17	0.20	0.13	0.24	0.26	0.20	0.13
Control mean	1.48	1.21	0.61	0.15	1.40	6.54	0.21	0.12
R-squared	0.13	0.14	0.23	0.27	0.22	0.19	0.22	0.30
Observations	264	264	264	264	264	264	264	264

Notes: This table reports treatment effects on pesticide residues. The results use MRL data for each pesticide (active ingredient) collected from each country. Columns 1-4 use the sum of incidences of pesticide residue exceeding the its MRL by country. Columns 5-8 use the unconditional mean residue amount scaled by the pesticide's MRL for each country. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 7: Treatment Effects on Standardized Product Attributes

	Sweetness	Skin	Bract	Length	Width	Weight	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Farmer Training	0.085	-0.006	-0.027	-0.175	0.136	-0.115	-0.017
	(0.162)	(0.083)	(0.116)	(0.114)	(0.090)	(0.101)	(0.050)
	[0.439]	[0.948]	[0.850]	[0.158]	[0.217]	[0.412]	[0.773]
Intermediary Training	0.146	0.022	-0.110	-0.136	0.051	-0.215	-0.040
	(0.156)	(0.083)	(0.089)	(0.164)	(0.116)	(0.109)	(0.054)
	[0.521]	[0.629]	[0.273]	[0.600]	[0.384]	[0.157]	[0.676]
Joint Training	0.274	0.063	0.106	-0.075	0.016	-0.154	0.038
	(0.155)	(0.079)	(0.101)	(0.130)	(0.093)	(0.085)	(0.051)
	[0.134]	[0.310]	[0.144]	[0.902]	[0.667]	[0.333]	[0.088]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.21	0.39	0.27	0.41	0.13	0.69	0.37
Control mean (in raw units)	16.43	3.99	4.25	14.35	8.44	522.49	-0.02
R-squared	0.37	0.14	0.12	0.32	0.27	0.43	0.35
Observations	2186	2186	2186	2186	2186	2186	2186

Notes: This table reports treatment effects on product attributes. The results use data from two follow-up survey rounds. Each product attribute is standardized by the control group's mean and standard deviation. Column 7 uses the average of the six standardized product attributes. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 8: Relationship Between Product Quality and GAP Compliance

	Pesticide Residue		Product Attributes						
	> MRL	Mean	Sweetness	Skin	Bract	Length	Width	Weight	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equipment and Area Management	-0.066	-0.011	0.065**	-0.034	0.036	-0.029	-0.020	-0.004	0.002
	(0.042)	(0.054)	(0.022)	(0.022)	(0.024)	(0.021)	(0.022)	(0.016)	(0.010)
Hygiene and Safety Management	-0.103**	-0.040	-0.001	0.033	0.006	-0.029	-0.007	-0.017	-0.003
	(0.045)	(0.056)	(0.027)	(0.023)	(0.022)	(0.020)	(0.022)	(0.019)	(0.012)
Soil, Water, and Waste Management	-0.116**	-0.173**	-0.068*	0.038	0.064*	0.036	0.032	0.021	0.021*
	(0.047)	(0.070)	(0.024)	(0.024)	(0.026)	(0.023)	(0.026)	(0.017)	(0.012)
Pesticide Management	-0.638***	-0.691***	0.043	-0.003	0.023	0.014	0.021	0.006	0.018
	(0.039)	(0.060)	(0.022)	(0.024)	(0.020)	(0.022)	(0.021)	(0.018)	(0.011)
Fertilizer Management	-0.015	0.011	0.033	-0.006	0.007	0.007	-0.000	-0.005	0.006
	(0.045)	(0.060)	(0.021)	(0.024)	(0.023)	(0.020)	(0.018)	(0.019)	(0.011)
Mean	1.31	0.97	16.54	3.99	4.27	14.24	8.48	513.76	-0.02
R-squared	0.64	0.61	0.37	0.15	0.12	0.32	0.27	0.43	0.34
Observations	264	264	2186	2186	2186	2186	2186	2186	2186

Notes: This table reports estimation results on the relationship between product quality and GAP compliance. Pesticide residue was measured during the second follow-up survey round with randomly sampled farmers. GAP audit scores and measurements on product attributes are collected from both follow-up survey rounds. Standard errors are clustered by farmer group and reported in parentheses. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 9: Treatment Effects on Export Performance

	Market (= 1 if Volume > 0)				Log(Volume)				
	Domestic	China	Asia	EU/US	Domestic	China	Asia	EU/US	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Farmer Training	-0.029	-0.001	0.042	-0.008	-0.235	-0.033	0.382	-0.046	0.009
	(0.017)	(0.044)	(0.033)	(0.013)	(0.146)	(0.396)	(0.294)	(0.112)	(0.061)
	[0.152]	[0.980]	[0.255]	[0.510]	[0.166]	[0.942]	[0.246]	[0.658]	[0.871]
Intermediary Training	0.001	-0.003	0.043	-0.003	0.011	-0.079	0.386	-0.012	-0.006
	(0.018)	(0.043)	(0.036)	(0.013)	(0.156)	(0.386)	(0.313)	(0.113)	(0.067)
	[0.707]	[0.861]	[0.353]	[0.865]	[0.694]	[0.755]	[0.334]	[0.807]	[0.949]
Joint Training	-0.026	-0.115*	0.194***	-0.005	-0.215	-0.970*	1.670***	-0.025	0.069
	(0.016)	(0.047)	(0.041)	(0.014)	(0.135)	(0.415)	(0.357)	(0.123)	(0.053)
	[0.088]	[0.003]	[0.001]	[0.934]	[0.104]	[0.007]	[0.001]	[0.826]	[0.070]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.86	0.00	0.00	0.79	0.85	0.00	0.00	0.83	0.26
Control mean (in levels)	0.03	0.93	0.05	0.01	0.13	5.88	0.28	0.05	6.35
R-squared	0.04	0.10	0.12	0.12	0.05	0.10	0.12	0.12	0.45
Observations	2179	2179	2179	2179	2179	2179	2179	2179	2184

Notes: This table reports treatment effects on farm export performances. The results use data from two follow-up survey rounds. The dependent variables in columns 1-4 are indicator variables equal to one if farmer sold product to respective market and zero otherwise. The dependent variables in columns 5-8 use volume sold to each market. Column 9 uses total volume sold by farmer. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 10: Market Destination and Product Quality

	Product's Market Destination			
	China	Asia	EU/US	Domestic
	(1)	(2)	(3)	(4)
GAP compliance	-0.051***	0.047***	0.011***	-0.006**
	(0.008)	(0.008)	(0.003)	(0.003)
Sweetness	-0.001	-0.001	0.004	-0.002
	(0.007)	(0.005)	(0.003)	(0.003)
Skin	0.003	0.001	-0.002	-0.002
	(0.007)	(0.005)	(0.003)	(0.003)
Bract	0.005	-0.001	-0.004**	-0.000
	(0.005)	(0.005)	(0.002)	(0.003)
Length	0.001	-0.004	0.004	-0.001
	(0.008)	(0.007)	(0.003)	(0.003)
Width	-0.013**	0.008	0.005	0.001
	(0.006)	(0.008)	(0.004)	(0.002)
Weight	-0.012	0.016*	-0.005	-0.000
	(0.010)	(0.009)	(0.004)	(0.003)
Pseudo R-squared	0.21	0.21	0.21	0.21
Observations	2732	2732	2732	2732

Notes: This table reports marginal effect estimates from a multinomial logit regression of market destination on product characteristics. The results use farm-gate sales data from two follow-up survey rounds. Each column represents one of four (broadly defined) market destinations the product could be sold to. Standard errors are clustered by farmer group and reported in parentheses. GAP compliance is the standardized score on the GAP audit. All product characteristics are standardized by the control group's mean and standard deviation. All specifications include farmer characteristics (age, female, education, experience, size of farm, time discounting, raven matrices score, received agricultural certificate, self-reported GAP compliance) at baseline as well as strata fixed effects, survey round fixed effects, and treatment group fixed effects. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 11: Treatment Effects on Farm Sales

		Revenue			Seasonal Profit		Annual Profit	
	Price	Direct	Implied	Cost	(2)-(4)	(3)-(4)	(2)-(4)	(3)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmer Training	0.033	0.039	-0.367	0.123	-0.011	-0.047	-0.032	-0.013
	(0.023)	(0.091)	(0.232)	(0.081)	(0.122)	(0.105)	(0.173)	(0.130)
	[0.291]	[0.683]	[0.218]	[0.296]	[0.884]	[0.568]	[0.788]	[0.933]
Intermediary Training	-0.005	0.018	-0.094	0.057	-0.049	-0.067	0.055	0.036
	(0.020)	(0.092)	(0.192)	(0.064)	(0.155)	(0.141)	(0.163)	(0.144)
	[0.810]	[0.619]	[0.684]	[0.358]	[0.906]	[0.845]	[0.604]	[0.825]
Joint Training	0.103***	0.161	0.446**	0.160*	0.119	0.081	0.179	0.208
	(0.024)	(0.078)	(0.160)	(0.061)	(0.115)	(0.107)	(0.147)	(0.128)
	[0.001]	[0.002]	[0.001]	[0.007]	[0.135]	[0.104]	[0.096]	[0.043]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.00	0.07	0.00	0.64	0.06	0.09	0.05	0.00
Control mean (in levels)	12.43	81.06	79.43	41.27	58.65	58.49	97.05	96.48
R-squared	0.31	0.44	0.15	0.54	0.17	0.17	0.32	0.33
Observations	2179	2184	2201	2200	2076	2091	1087	1085

Notes: This table reports treatment effects on farm sales. The results use data from two follow-up survey rounds. All dependent variables are converted to log scales. Price is derived as the average of prices sold to intermediaries within each survey round weighted by the share of total volume sold to each intermediary. Direct revenue uses farmer reports on revenue and Derived revenue is the sum of the product of price and volume sold to each intermediary reported in the survey. Cost is the total cost of inputs excluding own work hours. Profit in column 5 is derived by subtracting cost from direct revenue and profit in column 6 is derived by subtracting cost from derived revenue. Profits in columns 7 and 8 are derived as annual revenue - annual cost. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 12: Price Premium - Market Destination and Quality

	Log (Farm-gate price)				
	OLS				IV
	(1)	(2)	(3)	(4)	(5)
Asia (excluding China)	0.287***		0.280***	0.289***	0.248***
	(0.021)		(0.021)	(0.021)	(0.025)
EU/US	0.335***		0.330***	0.340***	0.298***
	(0.033)		(0.038)	(0.039)	(0.042)
Domestic	-0.228***		-0.220***	-0.222***	-0.201***
	(0.029)		(0.028)	(0.028)	(0.032)
GAP compliance		0.021***	0.005	0.010**	0.068***
		(0.005)	(0.005)	(0.005)	(0.018)
Sweetness		0.004	0.003	0.003	0.002
		(0.005)	(0.004)	(0.004)	(0.004)
Skin		0.033***	0.032***	0.031***	0.031***
		(0.005)	(0.005)	(0.005)	(0.005)
Bract		-0.003	0.000	0.001	-0.002
		(0.004)	(0.004)	(0.004)	(0.004)
Length		-0.006	-0.006	-0.006	-0.005
		(0.007)	(0.006)	(0.006)	(0.006)
Width		0.014**	0.008	0.007	0.008
		(0.005)	(0.005)	(0.005)	(0.005)
Weight		0.009	0.006	0.007	0.007
		(0.008)	(0.008)	(0.008)	(0.007)
Treatment Group FE	Yes	Yes	Yes	No	No
First stage F-test					13.58
R-squared	0.40	0.29	0.42	0.41	0.35
Observations	2739	2733	2732	2732	2732

Notes: This table reports estimates from an ordinary least squares regression of price on product characteristics. The results use farm-gate sales data from two follow-up survey rounds. Farm-gate price is the price farmer received in each sales transaction. Standard errors are clustered by farmer group and reported in parentheses. China market is omitted in specification. GAP compliance is the standardized score on the GAP audit. All product characteristics are standardized by the control group's mean and standard deviation. All specifications include farmer characteristics (age, female, education, experience, size of farm, time discounting, raven matrices score, received agricultural certificate, self-reported GAP compliance) at baseline as well as strata fixed effects, survey round fixed effects, and treatment group fixed effects. * denotes statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 13: Treatment Effects on Farm Input Costs

	Log transformed							
	Fertilizer	Pesticide	Facility	Equipment	Labor	Utility	Total	Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmer Training	-0.147	0.171	0.538*	0.332	0.117	0.016	0.123	0.150
	(0.169)	(0.120)	(0.191)	(0.739)	(0.235)	(0.113)	(0.081)	(0.159)
	[0.500]	[0.384]	[0.006]	[0.716]	[0.716]	[0.903]	[0.287]	[0.468]
Intermediary Training	0.081	0.033	0.081	-0.016	-0.024	-0.009	0.057	-0.095
	(0.099)	(0.123)	(0.197)	(0.814)	(0.210)	(0.064)	(0.064)	(0.258)
	[0.156]	[0.827]	[0.877]	[0.817]	[0.982]	[0.949]	[0.365]	[0.715]
Joint Training	0.032	0.295*	0.945***	0.932	0.336	0.217*	0.160	0.133
	(0.122)	(0.114)	(0.241)	(0.820)	(0.205)	(0.082)	(0.061)	(0.139)
	[0.401]	[0.003]	[0.001]	[0.054]	[0.002]	[0.002]	[0.009]	[0.158]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.30	0.14	0.11	0.41	0.24	0.07	0.64	0.90
Control mean (in levels)	11.61	3.34	0.11	2.84	13.39	9.15	41.27	5.48
R-squared	0.17	0.26	0.13	0.20	0.15	0.29	0.54	0.25
Observations	2201	2201	2201	2200	2201	2201	2200	2201

Notes: This table reports treatment effects on farm input costs. The results use data from two follow-up survey rounds. All input costs, except respondent's work hour, are log transformed. Total is the sum of input costs through columns 1-6 and cost specified as other in the survey. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 14: Treatment Effects on Intermediary Knowledge and Business Outcomes

	GAP		Log(Price)		Log(Volume)			
	Knowledge	Facility	Purchase	Sell	Total	China	Asia	EU/US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmer Training	0.085	-0.063	-0.016	-0.013	-0.050	0.005	-0.081	0.013
	(0.160)	(0.118)	(0.018)	(0.011)	(0.080)	(0.095)	(0.156)	(0.016)
	[0.692]	[0.631]	[0.427]	[0.207]	[0.567]	[0.975]	[0.648]	[0.256]
Intermediary Training	0.443**	0.117	-0.021	-0.012	0.034	0.046	0.047	0.000
	(0.198)	(0.094)	(0.018)	(0.012)	(0.083)	(0.100)	(0.182)	(0.018)
	[0.132]	[0.375]	[0.407]	[0.455]	[0.744]	[0.720]	[0.807]	[0.935]
Joint Training	0.543***	-0.117	-0.004	0.001	-0.036	-0.059	0.140	0.046
	(0.161)	(0.102)	(0.016)	(0.011)	(0.072)	(0.092)	(0.167)	(0.025)
	[0.008]	[0.272]	[0.717]	[0.935]	[0.564]	[0.335]	[0.486]	[0.563]
Control mean	-0.00	-0.00	14.65	17.10	447.21	365.47	3.78	0.00
R-squared	0.36	0.77	0.86	0.89	0.81	0.65	0.68	0.88
Observations	201	201	368	368	368	368	368	368

Notes: This table reports treatment effects on intermediary's GAP knowledge, compliance, and business outcomes. The results use data from two follow-up survey rounds. Dependent variables on GAP are standardized by the control group's mean and standard deviation. Column 1 measures intermediary's knowledge on GAP based on a test consisting of 10 multiple choice questions conducted during first follow-up survey round. Column 2 measures intermediary's GAP compliance using facility audit performed by BTDC staff. Columns 3 and 4 uses the reported farm gate price purchased from farmers and facility gate price sold to buyers, respectively. Columns 5-8 are reports on volume exported sold to each market destination. All specifications include intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer-intermediary group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table 15: Treatment Effects on Intermediary Revenue, Cost, and Profit

	Revenue		Cost				Profit	
	Direct	Implied	Labor	Utility	Material	Total	(1)-(6)	(2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmer Training	-0.006	-0.009	0.050	0.016	0.164	0.048	0.009	0.097
	(0.138)	(0.106)	(0.146)	(0.169)	(0.314)	(0.116)	(0.137)	(0.109)
	[0.967]	[0.921]	[0.829]	[0.908]	[0.617]	[0.722]	[0.927]	[0.352]
Intermediary Training	0.194	0.136	0.053	0.230	0.449	0.201	0.080	-0.142
	(0.125)	(0.111)	(0.173)	(0.192)	(0.283)	(0.134)	(0.132)	(0.178)
	[0.247]	[0.370]	[0.773]	[0.254]	[0.271]	[0.234]	[0.560]	[0.584]
Joint Training	-0.004	-0.028	0.020	-0.104	0.169	0.001	-0.103	0.114
	(0.132)	(0.133)	(0.148)	(0.143)	(0.259)	(0.119)	(0.171)	(0.105)
	[0.986]	[0.858]	[0.900]	[0.436]	[0.482]	[0.980]	[0.727]	[0.276]
Control mean	1236.05	1187.44	335.35	331.28	342.33	1008.95	877.09	858.49
R-squared	0.76	0.81	0.57	0.64	0.68	0.75	0.20	0.28
Observations	368	368	368	368	368	368	350	350

Notes: This table reports treatment effects on intermediary's revenue, cost, and profits. The results use data from two follow-up survey rounds. Direct revenue uses intermediary reports on revenue and Derived revenue is the product of (average facility gate price - average farm gate price) and total volume sold in the survey. Cost is measured along three areas - hired labor, utility, and material (excludes dragon fruit purchase). Profit in column 7 is derived by subtracting cost from direct revenue and profit in column 8 is derived by subtracting cost from implied revenue. All specifications include intermediary characteristics at baseline as control variables as well as strata fixed effects and survey round fixed effects. Standard errors are clustered by farmer-intermediary group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

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Appendix

A Appendix Tables & Figures

Figure A-1: Dragon Fruit Production

(a) Dragon Fruit

(b) Dragon Fruit Farm

(c) Harvesting

(d) Loading for Shipment

Source: figure (a) is a picture of dragon fruit downloaded from Wikipedia page, figures (b), (c), and (d) are from authors.

Figure A-2: Map of Binh Thuan Province

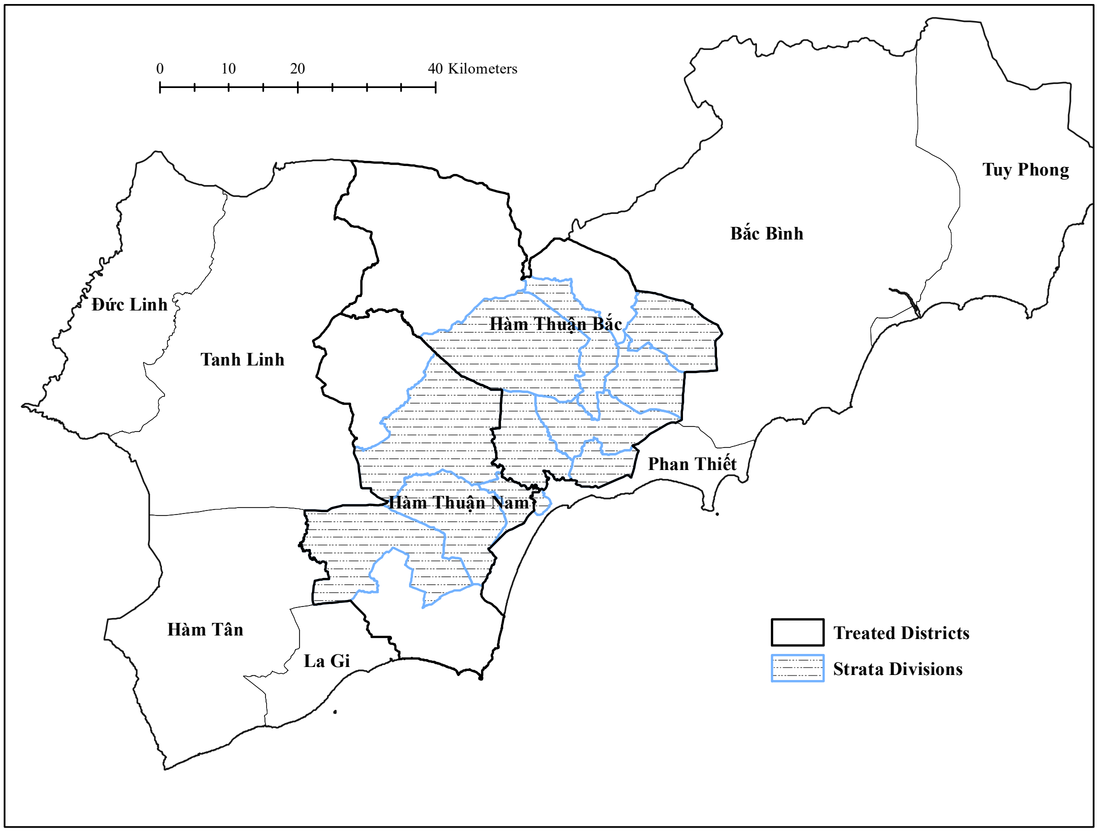


Figure A-3: VietGAP Checklist

VietGAP Checklist

Code	Requirements	Pass	Fail
C-1: Containers or storages of fertilizers, pesticides and other chemicals			
a	Chemical containers must be sealed, not leaked outside; warning signs of danger; If it is stored in a warehouse, the warehouse must have a lock and only authorized personnel should enter the warehouse		
b	Do not store or leave chemical containers in the preliminary processing area, living area or near water sources; do not store with other products		
c	Tools and materials need to be available in case of spillage of fertilizer, pesticides, and chemicals		
C-2: Equipment and machinery for production and preliminary processing			
	Must be cleaned before, after use and regular maintenance to avoid accidents for users and contaminate the product		
C-3: Diagram			
	There must be a diagram of the production area, place for storing fertilizer, pesticide, equipment, machinery, tools for production and preliminary processing (if any) and mark the surrounding area		
C-4: Tracking the production process			
a	Tracking list for purchased or self-produced input materials		
b	Tracking list for monitoring the production and consumption process		
C-5: Working conditions and personal hygiene			
a	Need to provide safe working conditions, including basic equipments necessary for protection and safety of workers		
b	Toilets, hand washing areas should be clean and have personal hygiene instructions		
c	Labor protection (clothes, gloves, makeup, boots, etc.) need to be cleaned before and after use and stored in a designated area and not kept togheter with pesticide, fertilizer and other chemicals		
d	First aid equipment and instructions are ready for use in case of emergency		
e	Workers need to follow protection guidelines suitable to their duty to limit the risk of contamination for products as well as health hazards.		
C-6: Soil, substrates, water and inputs			

a	In case of using chemicals to treat soil, substrates, and water must record time, method, chemical and isolation time (if any)		
b	It is necessary to have appropriate farming measures in accordance with soil and crop conditions; avoid environmental pollution and degradation of soil resources		
c	There should be safeguards to prevent and control leakage of pesticides and fertilizers		
d	The chemical and pesticide mixtures must be treated to ensure that they do not contaminate water sources and products		
e	The material of the substrate must have a clear origin and record of the composition of ingredient and supplements		
C-7: Varieties			
	Must use plant varieties of clear origin, which are permitted for production and trade in Vietnam or local varieties that have been produced and used for a long time without causing toxic harm to people. Need to select varieties that are resistant to pests and diseases and use healthy and clean seeds and seedlings to reduce the use of pesticides		
C-8: Fertilizers and supplements			
a	Fertilizers and supplements that are allowed to be produced and traded in Vietnam must be used		
b	If using animal and poultry manure as fertilizer, it must be composted and control for heavy metal as instructed		
c	Fertilizers and supplements must be kept in proper packaging; if changing the packaging, or storing in other containers the full name, instructions for use, expiry date should be specified as original packaging.		
C-9: Pesticides and chemicals			
a	It is necessary to apply integrated pest management (IPM) or integrated crop management (ICM) measures		
b	Use drug-containing pesticides on the list of permitted pesticides in Vietnam and apply according to the principle of true 4 (right medicine; right time; right concentration, dosage; right way) or follow the instructions of technicians and manufacturers		
c	Buy pesticides at stores that qualify for pesticide supply		
d	There must be warning signboards for newly sprayed areas		
e	Unused pesticides should be collected and treated according to hazardous waste regulations		
f	In case of storing and using fuels, gasoline, oil and other chemicals you must ensure: allowed for use; prevent contamination of other products and environment; safety for workers; prevention of fire		

g	Pesticides and chemicals must be kept in proper packaging; if changing the packaging, or storing in other containers the full name, instructions for use, expiry date should be specificed as the original packaging		
h	Chemicals that are not used or have expired must be collected and disposed of according to regulations. Store according to the instructions on the product packaging or according to the manufacturer's instructions		
C-10: Waste management			
a	Do not reuse packaging, fertilizer containers, pesticides, chemicals to contain products		
b	Used packages of pesticides and fertilizers must be collected and treated according to the law on environmental protection		
c	Waste during production and preliminary processing and waste from toilets must be collected and disposed of in accordance with environmental regulations		

Table A-1: Vietnamese Edible Fruit Exports by Country in 2015 and 2019

2015			2019		
Country	Value (1M USD)	Share (%)	Country	Value (1M USD)	Share (%)
China	459.31	84.17	China	1405.88	90.74
Thailand	13.87	2.54	USA	38.25	2.47
USA	12.92	2.37	France	20.67	1.33
Hong Kong	12.38	2.27	Hong Kong	13.41	0.87
Indonesia	6.9	1.27	Thailand	12.01	0.78
Canada	5.79	1.06	Netherlands	9.81	0.63
Netherlands	5.73	1.05	India	8.83	0.57
Japan	4.84	0.89	Canada	8.03	0.52
Singapore	4.09	0.75	United Arab Emirates	5.61	0.36
United Arab Emirates	3.43	0.63	Singapore	4.48	0.29

Source: Data obtained from UN Comtrade database. The table shows top 10 countries in terms of export volume of other Vietnamese edible fruit that is within the same category as dragon fruit. Examples of this category are lychee, longan and date.

Table A-2: Baseline Balance Check with Farmer Characteristics

Training treatment	No	Farmer	Interme-diary	Joint	No	Farmer	Interme-diary	Joint		
Certification treatment	No	No	No	No	Yes	Yes	Yes	Yes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	p-value	*N*
Age	46.17	-0.86	-1.35	-0.22	1.27	-1.26	0.48	-2.62	0.42	1,141
	(12.26)	(1.81)	(1.97)	(1.74)	(1.72)	(1.89)	(1.76)	(1.67)		
Female	0.41	0.00	-0.02	-0.04	-0.02	0.00	-0.04	-0.04	0.99	1,141
	(0.49)	(0.08)	(0.10)	(0.09)	(0.09)	(0.11)	(0.08)	(0.09)		
Secondary education	0.68	-0.03	-0.01	0.06	0.02	0.05	0.09	-0.05	0.99	1,141
	(0.47)	(0.16)	(0.16)	(0.18)	(0.17)	(0.17)	(0.17)	(0.13)		
Experience growing dragon fruit	11.70	-1.22	-1.53	-1.81*	-0.84	-1.47	-2.16**	-0.03	0.39	1,141
	(5.71)	(1.12)	(1.03)	(0.97)	(1.12)	(0.97)	(0.98)	(1.23)		
Size of dragon fruit farm	0.78	-0.06	-0.07	0.07	-0.03	-0.07	-0.03	0.12	0.64	1,141
	(0.70)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.06)	(0.09)		
Number of dragon fruit trees	829.3	-43.2	-25.2	122.5	-4.5	-38.1	-127.0*	-0.8	0.44	1,141
	(677.0)	(77.6)	(81.1)	(109.5)	(71.4)	(91.4)	(68.3)	(116.4)		
Received agricultural certificate	0.44	-0.02	-0.09	-0.15	0.05	-0.19	-0.03	-0.14	0.25	1,141
	(0.49)	(0.08)	(0.11)	(0.10)	(0.10)	(0.09)	(0.11)	(0.09)		
Ever received loan	0.62	0.08	-0.06	0.08	-0.01	-0.02	0.04	-0.01	0.42	1,141
	(0.49)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)		
Ever saved at bank	0.31	-0.10	-0.04	-0.03	-0.04	0.04	0.01	-0.03	0.66	1,141
	(0.47)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)		
Raven matrices score	4.13	-0.17	-0.03	-0.17	-0.32	-0.45	0.00	0.78	0.18	1,141
	(3.53)	(0.56)	(0.45)	(0.65)	(0.61)	(0.51)	(0.57)	(0.45)		
Time discounting: present biased	0.23	-0.06	0.02	0.00	0.01	0.06	-0.04	0.06	0.39	1,141
	(0.42)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)		
Self-reported GAP compliance	0.62	0.00	-0.02	-0.01	-0.01	-0.08**	-0.06	-0.02	0.25	1,141
	(0.20)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)		
Volume sold	11.36	0.21	-0.81	-1.06	-0.01	-2.04	-3.87	-3.81	0.62	1,141
	(11.90)	(2.78)	(2.51)	(2.42)	(2.91)	(2.39)	(2.87)	(2.80)		
Average price	10.53	-0.28	-0.35	0.43	0.00	-0.33	0.67	-0.78	0.84	1,141
	(3.52)	(0.94)	(0.96)	(1.16)	(0.97)	(1.01)	(1.09)	(1.00)		
Farmer's own work hours	6.66	0.09	0.34	-0.25	0.00	-0.02	-0.31	0.04	0.74	1,141
	(1.79)	(0.38)	(0.40)	(0.35)	(0.37)	(0.43)	(0.36)	(0.38)		
Fertilizer cost	29.6	1.32	3.21	5.68	0.19	-0.60	-6.45	-10.2	0.77	1,141
	(39.0)	(8.98)	(9.63)	(11.5)	(8.33)	(8.60)	(9.30)	(9.55)		
Pesticide cost	1.90	0.07	0.11	1.01	0.59	0.71	0.79	0.37	0.98	1,141
	(4.32)	(1.08)	(1.03)	(1.21)	(1.02)	(1.24)	(0.90)	(1.11)		
Facility cost	0.30	1.34	5.92	1.26	-0.49	2.01	0.34	-0.36	0.44	1,141
	(2.45)	(1.42)	(4.22)	(1.12)	(1.18)	(1.57)	(1.10)	(1.16)		
Equipment cost	5.01	-2.04	-1.83	-0.65	-0.31	-1.18	-0.85	-1.75	0.84	1,141
	(18.40)	(2.14)	(1.99)	(1.88)	(2.37)	(2.26)	(2.05)	(2.00)		
Labor cost	9.13	-4.02	-0.79	1.11	-0.46	3.92	4.93	-3.10	0.05	1,141
	(18.50)	(2.54)	(3.27)	(2.55)	(2.51)	(3.25)	(3.03)	(3.03)		
Utility cost	25.2	13.9	-4.20	11.7	7.63	-5.03	-16.5	-12.2	0.42	1,141
	(45.3)	(16.1)	(12.1)	(15.8)	(15.3)	(12.9)	(15.5)	(15.9)		
Total expenses	71.8	9.85	4.11	20.1	7.48	-0.09	-16.5	-27.8	0.71	1,141
	(90.0)	(23.7)	(22.1)	(28.0)	(22.8)	(22.1)	(23.7)	(27.1)		
Attrition in follow-up survey rounds										
First follow-up round	0.02	0.02	0.00	0.00	-0.01	0.03	0.03	0.03		
	(0.12)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)		
Second follow-up round	0.03	0.01	0.03	0.01	-0.01	0.06	0.03	0.04		
	(0.16)	(0.03)	(0.04)	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)		

Notse: This table shows balance checks for farmer characteristics across randomized treatment arms. Column 1 shows sample mean and standard deviation for the control group. Columns 2 through 8 show OLS regression coefficients of the other seven treatment group indicators. Column 9 shows the p-value for the Wald test of joint significance of the seven coefficients. Standard errors are in parentheses.

Table A-3: Baseline Balance Check with Intermediary Characteristics

Training treatment	No	Farmer	Interme-diary	Both	No	Farmer	Interme-diary	Both		
Certification treatment	No	No	No	No	Yes	Yes	Yes	Yes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	p-value	N
Years of business	9.63	5.47	0.26	-0.13	-0.45	0.23	-1.41	-1.80	0.29	228
	(5.47)	(1.34)	(1.19)	(1.56)	(1.36)	(1.50)	(1.23)	(1.17)		
Type = collector	0.41	0.18	-0.07	0.18	-0.05	0.04	-0.04	0.09	0.21	228
	(0.50)	(0.13)	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)	(0.13)		
Type = export enterprise	0.52	-0.11	0.11	-0.11	0.12	0.03	0.12	-0.02	0.23	228
	(0.51)	(0.13)	(0.11)	(0.11)	(0.10)	(0.12)	(0.12)	(0.13)		
Type = cooperative	0.07	-0.08	-0.04	-0.07	-0.07	-0.08	-0.07	-0.07	0.75	228
	(0.27)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)		
Size of packing facility (m^2)	1234.44	-374.96	86.67	-264.92	214.63	-102.47	323.60	-318.66	0.19	228
	(1371.91)	(289.92)	(347.76)	(327.05)	(309.38)	(321.20)	(341.00)	(320.41)		
Trade volume (tons)	455.56	-83.98	-35.57	-76.30	42.11	-0.91	-7.89	-89.24	0.39	228
	(366.13)	(88.98)	(95.06)	(96.64)	(83.30)	(96.55)	(87.98)	(85.43)		
Average purchase price	13.61	-0.16	-0.60	-0.65	-0.07	-0.25	-0.54	0.01	0.80	228
	(2.14)	(0.63)	(0.63)	(0.54)	(0.59)	(0.58)	(0.57)	(0.54)		
Average sales price	15.65	0.27	-0.06	-0.16	0.41	-0.14	-0.10	0.15	0.98	228
	(2.58)	(0.65)	(0.70)	(0.72)	(0.73)	(0.73)	(0.68)	(0.61)		
Self-reported GAP compliance	3.67	0.06	-0.41	0.23	-0.35	0.01	-0.70**	-0.28	0.03	228
	(1.39)	(0.36)	(0.34)	(0.36)	(0.41)	(0.31)	(0.33)	(0.40)		
Contract with buyer	0.42	-0.11	0.15	-0.08	0.08	-0.06	0.01	-0.09	0.32	228
	(0.49)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.10)	(0.13)		
Average experience with buyer	5.05	1.55**	0.98	0.45	-0.04	0.01	0.31	0.20	0.44	228
	(2.65)	(0.75)	(0.63)	(0.87)	(0.69)	(0.65)	(0.65)	(0.55)		
Volume of Chinese exports	369.75	-100.44	-59.45	-87.00	-51.89	-24.86	-41.97	-62.63	0.66	228
	(370.88)	(71.47)	(76.91)	(74.22)	(72.10)	(71.36)	(74.67)	(74.85)		
Volume of Asian exports	7.10	0.95	4.40	7.12	20.65*	3.78	6.54	-5.90	0.28	228
	(20.76)	(7.01)	(6.83)	(10.67)	(12.40)	(5.95)	(7.38)	(4.54)		
Volume of EU/US exports	0.00	0.02	0.21	0.24	0.77	0.07	0.19	3.32	0.96	228
	(0.00)	(0.74)	(0.63)	(0.62)	(1.06)	(0.71)	(0.63)	(2.87)		
Volume of domestic market	4.88	0.25	-4.18	-2.77	2.21	-1.08	-0.37	-2.22	0.51	228
	(16.96)	(3.94)	(3.15)	(3.20)	(4.46)	(3.08)	(3.61)	(3.21)		
Expenses on labor	427.04	-66.00	27.28	-13.77	13.74	0.38	88.52	9.10	0.86	228
	(293.03)	(85.41)	(86.46)	(99.91)	(84.26)	(88.33)	(101.85)	(89.71)		
Expenses on utility	320.07	-89.13	-13.92	-51.19	-6.78	-31.79	-27.77	-120.19	0.84	228
	(502.23)	(112.31)	(113.72)	(134.64)	(109.24)	(116.57)	(134.52)	(109.23)		
Expenses on materials	513.81	-166.52	-86.46	-180.35	120.02	174.69	15.18	-0.36	0.43	228
	(726.77)	(170.24)	(168.00)	(196.71)	(166.44)	(271.34)	(252.30)	(173.44)		
Attrition in follow-up survey rounds										
First follow-up round	0.15	-0.07	0.03	-0.06	0.00	-0.04	-0.05	-0.05		
	(0.36)	(0.08)	(0.10)	(0.09)	(0.08)	(0.08)	(0.09)	(0.07)		
Second follow-up round	0.26	-0.02	0.02	0.02	-0.07	-0.04	0.06	0.06		
	(0.45)	(0.10)	(0.12)	(0.12)	(0.10)	(0.12)	(0.10)	(0.10)		

Notes: This table shows balance checks with intermediary characteristics across randomized treatment arms. Column 1 shows sample mean and standard deviation for the control group. Columns 2 through 8 show OLS regression coefficients of the other seven treatment group indicators. Column 9 shows the p-value for the Wald test of joint significance of the seven coefficients. Standard errors are in parentheses.

Table A-4: Treatment Effects on Farmer's GAP Compliance - by Survey Round

	Audit report on Compliance					
	Total (1)	Equipment (2)	Hygiene (3)	Soil (4)	Pesticide (5)	Fertilizer (6)
Panel A. Six Months After Training Intervention						
Farmer Training	0.470***	0.310**	0.148	0.333**	0.428***	-0.065
	(0.107)	(0.112)	(0.095)	(0.116)	(0.078)	(0.119)
	[0.004]	[0.047]	[0.281]	[0.066]	[0.001]	[0.694]
Intermediary Training	0.157	0.114	0.012	0.203	0.139	-0.174
	(0.118)	(0.107)	(0.109)	(0.133)	(0.089)	(0.124)
	[0.141]	[0.163]	[0.386]	[0.259]	[0.143]	[0.282]
Joint Training	0.668***	0.418***	0.225*	0.436***	0.595***	0.046
	(0.144)	(0.138)	(0.104)	(0.147)	(0.091)	(0.113)
	[0.000]	[0.002]	[0.002]	[0.013]	[0.000]	[0.283]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.17	0.46	0.45	0.43	0.04	0.15
Control mean (Pass/Total)	0.71	0.58	0.79	0.70	0.69	0.89
R-squared	0.20	0.15	0.15	0.11	0.15	0.06
Observations	1099	1099	1099	1099	1099	1099
Panel B. Twelve Months After Training Intervention						
Farmer Training	0.403***	0.336***	0.171*	0.305***	0.231**	-0.133*
	(0.110)	(0.114)	(0.092)	(0.090)	(0.101)	(0.085)
	[0.004]	[0.063]	[0.090]	[0.036]	[0.072]	[0.264]
Intermediary Training	0.067	0.084	0.030	0.137	0.025	-0.244*
	(0.109)	(0.132)	(0.090)	(0.111)	(0.087)	(0.115)
	[0.454]	[0.352]	[0.279]	[0.344]	[0.966]	[0.128]
Joint Training	0.624***	0.464***	0.223**	0.361***	0.458***	0.015
	(0.102)	(0.096)	(0.078)	(0.109)	(0.083)	(0.080)
	[0.000]	[0.000]	[0.001]	[0.006]	[0.000]	[0.138]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.05	0.22	0.57	0.61	0.01	0.05
Control mean (Pass/Total)	0.74	0.63	0.83	0.74	0.72	0.92
R-squared	0.17	0.14	0.15	0.08	0.10	0.06
Observations	1084	1084	1084	1084	1084	1084

Notes: This table reports treatment effects on farmer's GAP knowledge, awareness of pesticide use, and GAP compliance. The results use data from two follow-up survey rounds: panel A shows the results from first follow-up survey and panel B shows the results from second follow-up survey. Dependent variables are standardized by the control group's mean and standard deviation. Column 1 uses total audit score which is the number of items passed across all 32 items. Columns 2-5 use number of items passed in each management category. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table A-5: Treatment Effects on Farm Input Costs - by Survey Round

	Log transformed							
	Fertilizer	Pesticide	Facility	Equipment	Labor	Utility	Total	Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Six Months After Training Intervention								
Farmer Training	-0.212	0.104	1.011**	0.600	0.475	0.036	0.168*	0.176
	(0.190)	(0.133)	(0.438)	(0.866)	(0.276)	(0.108)	(0.080)	(0.209)
	[0.363]	[0.652]	[0.006]	[0.433]	[0.656]	[0.782]	[0.182]	[0.755]
Intermediary Training	0.099	0.016	0.355	0.134	0.008	0.046	0.108	0.019
	(0.118)	(0.146)	(0.364)	(0.766)	(0.263)	(0.069)	(0.070)	(0.284)
	[0.409]	[0.967]	[0.574]	[0.958]	[0.926]	[0.474]	[0.182]	[0.732]
Joint Training	-0.059	0.213	2.165***	2.151	0.382	0.163	0.202**	-0.054
	(0.161)	(0.129)	(0.450)	(0.917)	(0.222)	(0.117)	(0.070)	(0.166)
	[0.854]	[0.042]	[0.001]	[0.012]	[0.004]	[0.101]	[0.002]	[0.769]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.47	0.21	0.03	0.10	0.68	0.21	0.68	0.18
Control mean (in levels)	10.08	3.29	0.21	3.53	10.47	8.72	37.18	5.38
R-squared	0.18	0.32	0.19	0.20	0.33	0.28	0.55	0.32
Observations	1099	1099	1099	1099	1099	1099	1099	1099
Panel B. Twelve Months After Training Intervention								
Farmer Training	-0.080	0.268	-0.065	-0.065	-0.023	-0.004	0.094	0.214
	(0.205)	(0.132)	(0.174)	(1.138)	(0.183)	(0.191)	(0.090)	(0.144)
	[0.688]	[0.255]	[0.511]	[0.983]	[0.964]	[0.984]	[0.406]	[0.324]
Intermediary Training	0.153	0.130	-0.119	0.244	-0.022	0.015	0.061	-0.202
	(0.132)	(0.135)	(0.165)	(1.329)	(0.193)	(0.108)	(0.075)	(0.254)
	[0.310]	[0.695]	[0.247]	[0.802]	[0.806]	[0.598]	[0.907]	[0.222]
Joint Training	0.175	0.381**	-0.157	0.044	0.105	0.256**	0.099	0.269
	(0.165)	(0.126)	(0.178)	(1.075)	(0.146)	(0.089)	(0.061)	(0.163)
	[0.188]	[0.000]	[0.121]	[0.709]	[0.222]	[0.001]	[0.116]	[0.007]
P-value ($H_0 : \beta_{\text{farmer}} = \beta_{\text{joint}}$)	0.23	0.27	0.26	0.90	0.50	0.13	0.95	0.68
Control mean (in levels)	13.16	3.39	0.01	2.15	16.34	9.59	45.39	5.57
R-squared	0.27	0.39	0.04	0.29	0.36	0.39	0.67	0.29
Observations	1084	1084	1084	1083	1084	1084	1083	1084

Notes: This table reports treatment effects on farm input costs. The results use data from two follow-up survey rounds: panel A shows the results from first follow-up survey and panel B shows the results from second follow-up survey. All input costs, except respondent's work hour, are log transformed. Total is the sum of input costs through columns 1-6 and cost specified as other in the survey. All specifications include farmer and intermediary characteristics at baseline as control variables as well as strata fixed effects. Standard errors are clustered by farmer group and reported in parentheses. P-values from randomization inference are reported in square brackets. * denotes false discovery rate controlled statistical significance at 0.10, ** at 0.05, and *** at 0.01.

Table A-6: Test difference between control farmers in treated and untreated districts

	Mean of	Treated − Untreated			
	Untreated	Coefficient	S.E.	p-value	Obs.
Panel A. Baseline Characteristics					
Age	46.38	-0.310	2.161	0.887	373
Female	0.60	-0.232	0.228	0.320	373
Secondary Education	0.71	-0.045	0.088	0.611	373
Experience growing dragon fruit	10.14	1.877	1.361	0.181	373
Number of dragon fruit trees	938.33	-172.39	86.41	0.058	373
Volume sold	13.15	-0.082	0.174	0.642	373
Average price	14.57	-0.178	0.088	0.054	373
Total expenses on inputs	135.00	0.035	0.575	0.952	373
Panel B. Technology Adoption and Quality Upgrading					
Knowledge	5.29	0.001	0.150	0.997	367
Awareness	3.72	-0.195	0.159	0.233	365
Compliance (Total)	0.67	0.409	0.112	0.001	732
Num. of residues exceeding MRL					
E.U.	1.50	-0.576	0.482	0.244	72
U.S.	1.00	-0.175	0.436	0.691	72
Japan	0.33	-0.037	0.496	0.941	72
China	0.00	0.012	0.164	0.943	72
Mean Product Attribute	0.05	-0.044	0.087	0.620	726
Panel C. Market Destination (= 1 if volume > 0) and Sales					
Domestic	0.07	-0.037	0.029	0.206	723
China	0.99	-0.083	0.042	0.060	723
Asia	0.03	0.054	0.034	0.131	723
EU/US	0.00	0.017	0.012	0.179	723
Average price	12.60	-0.043	0.020	0.042	723
Direct revenue	99.49	-0.040	0.083	0.634	723
Total expenses on inputs	46.01	0.169	0.077	0.039	723
Seasonal profit	72.63	0.110	0.231	0.637	676

Notes: This table reports differences in baseline characteristics and follow-up survey outcomes between control group farmers in treated districts and untreated districts (outside the two districts in which training intervention was implemented). Specifications include farmer characteristics at baseline as control variables and survey round fixed effects. Standard errors are clustered by farmer group.

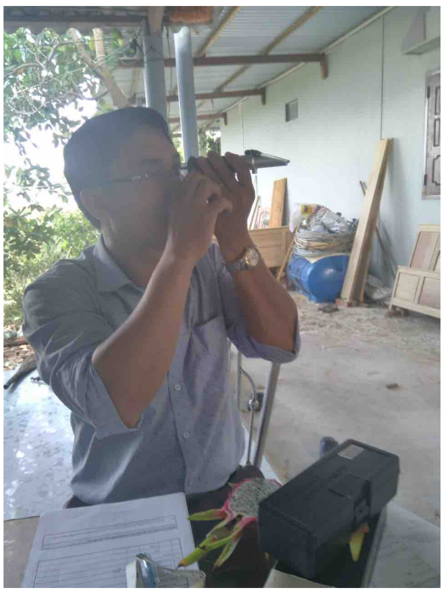
B Product Assessment

This section provides details on the assessment methods used in the followup surveys. We assess a product's observable characteristics mainly along four dimensions: (a) sweetness, (b) appearance, (c) size, and (d) weight. Next, we illustrate the tools and assessment standards used by surveyors for each dimension.

B.1 Sweetness

To measure sweetness of the fruit we use Degrees Brix – or total soluable content – which is commonly used by winemakers and fruit growers as a measurement of sugar level in fruits. A higher degree of Brix indicates higher sugar level and sweeter taste. Brix can be measured using a refractometer by squeezing fruit juice onto the surface of the refractometer and viewing the juice through light. We sampled fruit juice from three different parts of the fruit (top, middle, bottom) and use the mean Brix level as a measure of sweetness. Figure B-1 shows an image of a surveyor using the refractometrer and an image of parts of the fruit from which the juice sample is taken.

Figure B-1: Measuring sweetness of dragon fruit



(a) Surveyor using refractometer

(b) Sample from top, middle, and bottom

B.2 Appearance - skin and bract

Surveyors assessed the fruit's appearance by rating the skin and bract on a 0-5 point scale. To obtain consistent ratings across surveyors we attached descriptions to each rating that surveyors could use when assessing the fruit. Table B-1 shows the descriptions of the ratings used for the assessment.

Table B-1: Appearance assessment ratings and descriptions

	Rating	Description
Skin	0	Uneven red and translucent skin, many black/brown spottings
	1	Uneven red and translucent skin, some black/brown spottings
	2	Slightly pale red or dark skin, some black/brown spottings
	3	Light red or slightly dark skin, little black/brown spottings
	4	Evenly red and shiny skin, little black/brown spottings
	5	Evenly red and shiny skin, no black/brown spottings
Bract	0	Yellow color and withered
	1	Dark red, slightly yellow, withered at the edges
	2	Mix of yellow and red, no withering
	3	Slightly dark red, smooth texture
	4	Mix of red and green, smooth texture
	5	Bright green, glossy and smooth texture

B.3 Size and Weight

We use a vernier caliper to measure the length and width of the main part of the fruit. We use a portable scale to measure the weight of the fruit. Figure B-2 shows images of surveyors measuring the size and weight with the respective tools.

Figure B-2: Measuring size and weight of dragon fruit

(a) Surveyor using vernier caliper (b) Surveyor using portable scale

C Pesticide Residue Analysis

Table C-1 presents the list of 18 pesticides, or active ingredients, that we tested in this study.[49] Based on the list of permitted pesticides issued annually by Vietnam's Ministry of Agriculture and Rural Development MARD (2019), among the 18 pesticides, 17 pesticides were permitted for use in agriculture in Vietnam while 1 pesticide was not permitted for agricultural use. Pesticides can be grouped according to World Health Organization (WHO)'s hazard classification rule. Nine out of eighteen pesticides tested in this study are classified as moderately harzardous, two pesticides as slightly hazardous, and three pesticides as unlikely to cause an acute hazard. There are four pesticides without a hazard classification.

The last four columns show the MRL of each pesticide by country. In the main analysis, we use EU's MRL as the benchmark to test pesticide residue compliance due to two reasons: First, we believe that EU's MRL is most accurate. Its database allows the user to find MRL for a narrow subcategory of a fruit (i.e. MRL for dragon fruit is found in the cactus fruit group) whereas other country databases most likely provide MRLs only at large categories (i.e. MRL for dragon fruit is found in tropical-inedible group which includes a number of fruit groups). Second, compared to other countries, EU's MRL are more conservative and often considered to be of high standard in the food trading industry. According to interviews with exporters, most overseas buyers require EU MRLs for pesticide residue testing. Nevertheless, we also present results using MRLs for U.S., Japan, and China.

[49]The active ingredient (AI) in a pesticide is the chemical that actually causes the effect while the rest of the pesticide product is inert ingredients, such as water and additives.

Table C-1: Tested Pesticides - Hazard Classiciation and Maximum Residue Limit

		WHO	Maximum Residue Level (mg/kg)			
No	Pesticide Name	Hazard Classification	E.U.	U.S.	Japan	China
Permitted for use in agriculture under Vietnam regulation						
1	Chlorpyrifos	II	0.01	0.1	0.05	2
2	Difenoconazole	II	0.15	1.5	0.07	0.05
3	Fipronil	II	0.005	0.01	0.005	0.02
4	Metalaxyl	II	0.01	4	0.2	0.2
5	Permethrin	II	0.05	1	2	2
6	Phenthoate	II	0	0.01	0.1	1
7	Prochloraz	II	0.05	0.01	0.05	7
8	Quinalphos	II	0.01	0.01	0.02	0.5
9	Tebuconazole	II	0.01	0.05	0.1	0.05
10	Hexaconazole	III	0.01	0.01	0.2	0.05
11	Thiabendazole	III	0.02	3	3	3
12	Azoxystrobin	U	0.3	2	1	0.3
13	Chlorothalonil	U	0.01	0.5	0.2	0.2
14	Acetamiprid	UK	0.01	0.5	0.2	2
15	Cyprodinil	UK	0.02	2	0.3	0.5
16	Dithiocarbamates	UK	0.05	0.01	0.6	2
17	Pyraclostrobin	UK	0.02	0.04	0.02	0.05
Not permitted for use in agriculture under Vietnam regulation						
18	Carbendazim	U	0.1	0.01	2	0.5

Notes: This table provides the list of pesticides tested in the residue analysis. Vietnam's regulation is based on 2019's permitted list of pesticides for use in agriculture (Ministry of Agriculture and Rural Development, 2019). Hazard classification is based on World Health Organization's recommended classification of pesticides (WHO, 2009). Hazard classification indicators: II - moderately hazardous, III - slightly hazardous, U - unlikely hazardous, UK - classification is unavailable. Maximum Residue Level (MRL) is the highest level of a pesticide residue that is legally tolerated in a food when pesticides are applied correctly. E.U. MRLs are obtained from the European Commission MRL database (EC, 2019). Pesticide MRL marked with 0 indicates disapproval of use in agriculture.

D Detailed proofs

D.1 Intermediaries Pricing Strategy

For export intermediaries, the optimal price and number of offers solve the following:

$$\max_{v,p}\{v\pi(p) - c(v)\}$$

where $\pi(p)$ is the expected profit per offer.

Export intermediaries' problem can be decomposed as follows: first choosing price p and then choosing numbers of farmers to contact.

$$\max_{v,p}\{v\pi(p) - c(v)\} = \max_{v}\{v\max_{p}\{\pi(p)\} - c(v)\} = \max_{v}\{v\pi^*(p) - c(v)\}$$

where $\pi(p)$ is the expected profit per offer and $\pi^*(p)$ is maximal expected profit per offer. With probability $H(p)$, an export intermediary offers the highest price and can purchase one unit from a farmer.

$$H(p) = \sum_{z=0}^{\infty}\frac{e^{-\theta}\theta^z}{z!}[F(p)]^z = e^{-\theta(1-F(p))}$$

He or she sells at P^E on export market if the product quality exceeds the standard and gets nothings if it fails to pass the requirement. Therefore, the expected profit per offer also depends on expectation that the product is qualified and will be accepted by export market, β. Then $\pi(p)$ is given as follows

$$\pi(p) = (\beta P^E - p)H(p) = (\beta P^E - p)e^{-\theta(1-F(p))}$$

As in Mortensen (2003), there is no symmetric pure strategy equilibrium. Export intermediaries instead follow a mixed strategy, choosing price p from range $[p^{\min}, p^{\max}]$. Export intermediaries randomizing over price dispersion implies their expected profit per offer are equalized for any price in the support. The lower bound of price support $p^{\min} = P^D$, as none of price below will be accepted by farmers. Utilizing these two facts and equalizing expected profit for any price in the support, we derive the distribution of price offers

$$\pi(p) = \pi(P^D) = (\beta P^E - P^D)e^{-\theta} \Rightarrow F(p) = \frac{1}{\theta}\ln\left(\frac{\beta P^E - P^D}{\beta P^E - p}\right) \tag{8}$$

Then the upper bound of price support $p^{\max} = (1 - e^{-\theta})\beta P^E + e^{-\theta}P^D$. which is a convex combination of export and domestic market prices. It is always strictly below export price P^E, the price farmers can get under perfect information and perfect competition.

Given the optimal price to offer, optimal numbers of farmers are solved. Export intermediaries choose the number of offers to send such that the marginal cost of contacting one more farmer equals marginal benefit

$$v = \pi^*(p) = (\beta P^E - P^D)e^{-\theta} \tag{9}$$

As $\pi^*(p)$ are the same for every price p and thus are the same for all export intermediaries, they contact the same number of farmers. They send more offers if expected profit from one farmer is higher.

In the first stage, intermediaries make entry decisions based on expected profits of export deals. They will enter such that they are indifferent between being local and export intermediaries.

$$\pi^*(p)\pi^*(p) - c(\pi^*(p)) = f \Leftrightarrow \theta = \ln(\frac{\beta P^E - P^D}{\sqrt{2f}}) \tag{10}$$

If entry barrier is higher (f increases) or quality of export products worsens (β decreases), there are fewer intermediaries on the export market and they possess stronger market power.

D.2 Farmers' Market Decision and Input Decision

Farmers intending to export will choose input to maximize expected profit $U(E(p), k, i)$ given intermediaries strategy.

$$\max_i U(E(p), k, i) = \Phi(q)E(p) + [1 - \Phi(q)]P^D - c(i)$$
$$s.t.\ q = ki$$

With $\Phi(q)$, farmers can send a qualified signal and receive expected price from export intermediaries $E(p)$. Otherwise with bad signal, they can only turn back to the local market and get P^D. The unconditional expected price depends on the level of intermediation and expectation about the quality. The optimal input a farmer with efficiency k will put into production, $i(k, E(p))$ solves the following condition

$$i = \frac{k}{\sigma\sqrt{2\pi}} e^{-\frac{(Q^* - ki)^2}{2\sigma^2}} (E(p) - P^D) \tag{11}$$

It is not necessarily farmers with higher efficiency input more into production $i_k(k, E(p)) >=< 0$. For one thing, more efficient farmers use fewer input than less efficient farmers to produce the same quality product. For another thing, more efficient farmers will produce higher quality.

The price farmers expect to get, conditional on they send qualified signals is given by

$$\begin{aligned} E(p) &= (1 - H(P^D)) \int_{p_{\min}}^{p^{\max}} \frac{pdH(p)}{1 - H(P^D)} + H(P^D)P^D \\ &= [1 - e^{-\theta}(1 + \theta)]\beta P^E + e^{-\theta}(1 + \theta)P^D \end{aligned} \tag{12}$$

It is weighted average of domestic price P^D and effective export price βP^E and thus strictly below P^E which they can get under perfect competition and perfect information. Farmers expect to receive higher price as the level of intermediation θ increases and thus there are more competition among intermediaries.