

|        |                        |
|--------|------------------------|
| 申<br>报 | 系列：教师系列<br>教学科研并重<br>型 |
|        | 专业：农业经济<br>管理          |
|        | 职称：副教授                 |

## 业绩成果材料

（申报人的业绩成果材料包括论文、科研项目、获奖以及其他成果等）

单 位（二级单位） 经济管理学院

姓 名 蔡轶

材料核对人：

单位盖章：

核对时间：

华南农业大学制

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## 一、教学研究业绩

### 1. 编写教材：《农业技术经济学》



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## 二、科研项目

1. 主持：关于广东省哲学社会科学规划 2021 年度青年项目的立项通知（合同）及有关佐证材料

# 广东省哲学社会科学规划领导小组办公室

粤社科规办通（2021）41 号

## 广东省哲学社会科学规划 2021 年度项目 立项通知书

蔡轶同志：

经专家评审及省哲学社会科学规划领导小组审批，您申报的广东省哲学社会科学规划 2021 年度青年项目《乡村数字化减贫路径与优化对策研究》获准立项，批准号：GD21YYJ06，资助经费 5.0 万元，第一次拨款 3.5 万元，预留经费 1.5 万元。请认真填写立项回执，并于 11 月 20 日前寄回我办。

填写立项回执后，项目申请书即成为立项协议，对项目负责人及其所在单位具有约束力。项目负责人所在单位

须对立项协议的履行承担保证责任。项目负责人及所在单位须了解和执行以下规定：

1.课题组须学习并遵守《广东省哲学社会科学规划项目管理办法》。对于出现违规行为的，我办依据《广东省哲学社会科学规划项目管理办法》的相关规定进行处理。

2.立项项目经费不再追加。课题组如不接受，我办将撤销该项目立项。而立项经费一经接受，课题组将不得以资助经费不足为由，擅自变更原设计的最终成果形式和内容。

3.项目经费分两次拨付，其中，预留经费将在项目通过鉴定结项后拨付。拨款账号、开户行、户名如有变动，须以书面形式及时告知我办，以便准确拨款。

4.项目研究过程中，如有变更项目负责人、延长完成时间、改变成果内容或形式、变更项目管理单位、变更或增补课题组成员、终止项目或撤销项目等重要事项，项目负责人或所在单位必须按要求填写《广东省哲学社会科学规划项目重要事项变更审批表》，及时报我办审批。

5.项目成果的鉴定结项由我办组织，实行匿名鉴定制度。项目鉴定结项所需材料及装印要求，详见“广东社科规划”网站。

6.成果鉴定等级分为优秀、良好、合格和不合格四个等次。不合格者即未能通过结项，不予拨付预留经费。项

目成果的最终鉴定等级均通过“广东社科规划”网站予以公布，并通知项目负责人所在单位。

以上规定，项目负责人及所在单位应严格遵守。如有异议，可不接受资助（在回执中注明），立项协议自行废止。

省社科规划办

地址：广州市天河北路 618 号广东社科中心 B 座 9 楼

电话：(020)83825078

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广东省哲学社会科学规划领导小组办公室

2021 年 10 月 25 日

办公室

## 结项证书

项 目 类 别：广东省哲学社会科学规划青年项目

（批准号：GD21YYJ06）

项 目 名 称：乡村数字化减贫路径与优化对策研究

负 责 人：蔡轶

证 书 号：GHQN2023092

项 目 成 员：易法敏 林家宝 陈 洋 朱朕龙 邓金浩

结 项 等 级：合格

本项目经审核准予结项，特发此证。

广东省哲学社会科学规划专项小组

二〇二三年十一月二十四日

办公室

2. 主持：关于 2020 年度广东省普通高校青年创新人才项目的立项通知（合同）及有关佐证材料

# 广东省教育厅

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粤教科函〔2020〕6号

## 广东省教育厅关于公布 2020 年度普通高校 认定类科研项目立项名单的通知

各有关高校：

为深入实施创新驱动发展战略，落实《广东省教育厅 广东省科学技术厅关于印发科教融合协同推进高校科技创新能力提升工作计划的通知》（粤教科函〔2019〕57号），2020年省教育厅结合“创新强校工程”组织开展科研项目认定工作。经学校评审、省教育厅组织审核，现将通过认定方式批准立项的2020年度特色创新和青年创新人才科研项目立项名单（见附件）下达各高校。

请各高校按照《广东省高等教育“创新强校工程”专项资金管理办法》（粤财教〔2014〕130号）及相关科研平台项目管理办法，统筹安排项目资金，加强资金管理，督促项目承担人按照项目申请书开展建设工作，协助解决项目实施过程中遇到的困难和问题，确保研究项目如期完成目标任务。

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附件：1.2020 年度广东省普通高校特色创新项目立项名单  
2.2020 年度广东省普通高校青年创新人才项目立项  
名单



（联系人及电话：黄俊彦，020-37628271；高庆，  
020-37627742）

**公开方式：**主动公开

校对人：高庆

— 2 —

| 序号 | 项目编号         | 项目名称                                  | 负责人姓名 | 所属学校     |
|----|--------------|---------------------------------------|-------|----------|
| 6  | 2020WQNCX006 | 农户数字资本形成与培育机制研究                       | 蔡轶    | 华南农业大学   |
| 7  | 2020WQNCX007 | 新时期网络舆情对大学生情感取向演化的模型研究                | 刘洋    | 华南农业大学   |
| 8  | 2020WQNCX008 | 交替传译停顿现象实证研究                          | 宁静    | 南方医科大学   |
| 9  | 2020WQNCX009 | 嵌入性理论视角下基于护理站构建社区失能老年人居家照护模式研究        | 孙晓宁   | 广州中医药大学  |
| 10 | 2020WQNCX010 | 粤港澳大湾区高校教师职称制度研究                      | 林姬伶   | 华南师范大学   |
| 11 | 2020WQNCX011 | 艺术教育在广东高校思政教育融合的实践与研究——以歌剧《江姐》（校园版）为例 | 李卢泰龙  | 华南师范大学   |
| 12 | 2020WQNCX012 | 城市节水政策的驱动机理、效果评价与路径优化研究               | 杜敏哲   | 华南师范大学   |
| 13 | 2020WQNCX013 | 汉语二语互动语用能力测评研究                        | 陈卓    | 广东外语外贸大学 |
| 14 | 2020WQNCX014 | 吉莲·克拉克威尔生态诗学研究                        | 许景城   | 广东外语外贸大学 |
| 15 | 2020WQNCX015 | 德语母语和二语句子产出中语序与递增加工的关系研究              | 吴晓钢   | 广东外语外贸大学 |
| 16 | 2020WQNCX016 | “一带一路”倡议下的中国对外投资空间格局及其演变机制研究          | 邹嘉龄   | 广东外语外贸大学 |
| 17 | 2020WQNCX017 | 贸易自由化背景下企业社会责任策略对出口贸易的影响机理及效应研究       | 刘乾    | 广东外语外贸大学 |
| 18 | 2020WQNCX018 | 法治视野下粤港澳大湾区建设主体角色定位研究                 | 谢宇    | 广东外语外贸大学 |
| 19 | 2020WQNCX019 | 基于RPA的高校财务报销业务优化研究                    | 林仰晴   | 广东外语外贸大学 |
| 20 | 2020WQNCX020 | 我国老年宜居社区政策的创新扩散                       | 褚勇强   | 广东财经大学   |
| 21 | 2020WQNCX021 | 基于“多规合一”改革的广东省县国土空间用途管制研究             | 黄文浩   | 广东财经大学   |

3. 主参：关于农业部国家荔枝龙眼产业体系项目的立项通知（合同）及有关佐证材料

编号：CARS-32-14

国家荔枝龙眼产业技术体系  
2023 年度任务书

岗位名称： 产业经济

岗位科学家： 齐文娥

岗位科学家依托单位： 华南农业大学

依托单位法定代表人： 刘雅红

农业农村部科技教育司

二〇二三年七月十五日

## 填写说明

1. 本任务书由国家荔枝龙眼产业技术体系、首席科学家、国家荔枝龙眼产业技术研发中心依托单位、研究室主任、岗位科学家及其依托单位联合签订。
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## 一、基本情况表

| (一) 岗位科学家情况 |                                |         |     |        |                                      |
|-------------|--------------------------------|---------|-----|--------|--------------------------------------|
| 岗位名称        | 产业经济                           |         |     |        |                                      |
| 岗位科学家       | 齐文娥                            | 性别      | 女   | 出生年月   | 197208                               |
| 职称          | 副教授                            | 学历      | 研究生 | 行政职务   | 无                                    |
| 工作单位        | 华南农业大学                         |         |     |        |                                      |
| 通讯地址/邮编     | 广东省广州市天河区五山路 483 号/510642      |         |     |        |                                      |
| 电话/电子信箱     | 13392621688/qiwene@scau.edu.cn |         |     |        |                                      |
| 所属功能研究室     | 产业经济                           |         |     |        |                                      |
| 功能研究室主任     | 齐文娥                            |         |     |        |                                      |
| (二) 团队成员情况  |                                |         |     |        |                                      |
| 姓名          | 学历/职称                          | 出生年月    | 性别  | 工作单位   | 电话/邮箱                                |
| 左两军         | 研究生/副教授                        | 1970-09 | 女   | 华南农业大学 | 13560024664<br>jenney@scau.edu.cn    |
| 贺梅英         | 研究生/副教授                        | 1977-12 | 女   | 华南农业大学 | 13544327358<br>meiyinghe@scau.edu.cn |
| 杨学儒         | 研究生/教授                         | 1980-05 | 男   | 华南农业大学 | 18924181009<br>yangxueru2005@126.com |
| 蔡轶          | 研究生/副教授                        | 1990-10 | 男   | 华南农业大学 | 18076594175<br>caiyi@scau.edu.cn     |

### 五、签约方

国家荔枝龙眼产业技术体系首席科学家（签字）：陈学利

年 月 日

国家荔枝龙眼产业技术研发中心依托单位：（公章）

依托单位法定代表人（签字）：

刘雅红

年 月 日

功能研究室主任（签字）：

年 月 日

岗位科学家（签字）：齐文斌

2023年7月15日

岗位依托单位：

依托单位法定代表人（签字）：

刘雅红

年 月 日

#### 4. 主参：关于国家自然科学基金面上项目的立项通知（合同） 及有关佐证材料

### 国家自然科学基金资助项目批准通知

#### （预算制项目）

张蓓 先生/女士：

根据《国家自然科学基金条例》、相关项目管理办法规定和专家评审意见，国家自然科学基金委员会（以下简称自然科学基金委）决定资助您申请的项目。项目批准号：72273046，项目名称：消费者食品安全风险响应与引导机制研究：以跨境电商为例，直接费用：44.00万元，项目起止年月：2023年01月至2026年12月，有关项目的评审意见及修改意见附后。

请您尽快登录科学基金网络信息系统（<https://isisn.nsf.gov.cn>），**认真阅读《国家自然科学基金资助项目计划书填报说明》并按要求填写《国家自然科学基金资助项目计划书》（以下简称计划书）**。对于有修改意见的项目，请您按修改意见及时调整计划书相关内容；如您对修改意见有异议，须在电子版计划书报送截止日期前向相关科学处提出。

请您将电子版计划书通过科学基金网络信息系统（<https://isisn.nsf.gov.cn>）提交，由依托单位审核后提交至自然科学基金委。自然科学基金委审核未通过者，将退回的电子版计划书修改后再行提交；审核通过者，打印纸质版计划书（一式两份，双面打印）并在项目负责人承诺栏签字，由依托单位科研、财务管理等部门审核、签章并在承诺栏加盖依托单位公章，且将申请书纸质签字盖章页订在其中一份计划书之后，一并报送至自然科学基金委项目材料接收工作组。纸质版计划书应当保证与审核通过的电子版计划书内容一致。**自然科学基金委将对申请书纸质签字盖章页进行审核，对存在问题的，允许依托单位进行一次修改或补齐。**

向自然科学基金委提交电子版计划书、报送纸质版计划书并补交申请书纸质签字盖章页截止时间节点如下：

1. **2022年10月8日16点：**提交电子版计划书的截止时间；
2. **2022年10月14日16点：**提交修改后电子版计划书的截止时间；
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国家自然科学基金委员会

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填表日期: 2022年09月09日

国家自然科学基金委员会制

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文件编号：粤基金字（2023）2号

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项目类别：广东省自然科学基金-面上项目

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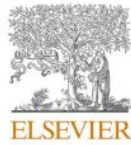
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# Effects of ICT-based extension service use on fertilizer knowledge and use efficiency: Evidence from litchi farmers in rural China

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## ARTICLE INFO

## Keywords:

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Fertilizer use efficiency  
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Rural China

## ABSTRACT

This study evaluates the treatment effects of ICT-based extension service (IES) use on fertilizer knowledge and use efficiency by employing survey data from 828 litchi farm households in southern China. An inverse probability weighted adjusted regression (IPWRA) model is applied to reduce potential selection bias. IPWRA model results indicate that IES use improves fertilizer effectiveness, procedural and declarative knowledge by 7.22%, 6.91%, and 4.95%, respectively. Moreover, IES users' fertilizer use efficiency is increased by 4.15%.

## 1. Introduction

Fertilizer plays a major role in Chinese intensive farming systems. According to the Food and Agriculture Organization (FAO), China's consumption of nitrogen (N), phosphate (P<sub>2</sub>O<sub>5</sub>), and potash (K<sub>2</sub>O) was 26.8, 10.3, and 10.4 million tons, respectively, in 2019. The excessive use of fertilizer results in global warming, soil acidification, and water eutrophication, which make agricultural systems more vulnerable (Ju et al., 2009). Therefore, improving fertilizer management is vital to environmental protection, food security, and climate change mitigation in China.

During the last decade, rapid penetration of information and communication technology (ICT) has occurred in developing countries. ICTs, especially the internet and smartphones, offer the low-cost delivery of ICT-based extension service (IES) (Aker, 2011; Aker et al., 2016). There is extensive literature devoted to the effects of IES use on fertilizer consumption (Arouna et al., 2021; Ding et al., 2022; W. Ma and Zheng, 2022; Ogutu et al., 2014; Yuan et al., 2021). The results depend on the context. For example, Ogutu et al. (2014) find evidence of the positive effect of IES adoption on fertilizer use in rural Kenya, where there is an urgent need to expand the use of modern materials to improve agricultural productivity and food security. In rural Nigeria, access to IES increases yields without increasing the intensity of fertilizer use (Arouna et al., 2021). In China, Yuan et al. (2021) find that internet use reduces chemical fertilizer use. Ma and Zheng (2022) find that smartphone use has a positive impact on the fertilizer expenditure of low-income wheat farmers and a negative impact on that of high-income wheat farmers. Another recent study indicated that IES use promotes site-specific fertilizer management technology adoption but does not reduce N fertilizer use among Chinese wheat farmers (Ding et al., 2022). However, less is known about the impact of IES use on fertilizer management ability.

This study adds to the literature by estimating the impact of IES use on fertilizer knowledge and use efficiency. The education level of aging farmers is generally low. The lack of adequate fertilizer knowledge is considered to be one of the main reasons for the overuse

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of fertilizer in rural China (Huang et al., 2008). There is plenty of evidence of the positive effects of conventional extension service access on reducing the overuse of fertilizer (Huang et al., 2012; Jia et al., 2013; Pan et al., 2017; Pan and Zhang, 2018). Compared with curriculum-based training, previous studies suggest that in-field guidance has larger effects on improving fertilizer knowledge and reducing the intensity of chemical fertilizer use (Huang et al., 2015; Pan et al., 2017). However, millions of smallholder farmers lack access to conventional extension services due to limited local government budgets. Moreover, fertilizer use efficiency reflects the relationship between fertilizer use intensity and farm output in a given production system (Reinhard et al., 1999). Improving farmers' fertilizer use efficiency helps them achieve a higher level of output without increasing the amount of fertilizer use. It thus contributes to sustainable agricultural development.

We used a dataset that covers 828 Chinese litchi growers. Chinese farmers have grown litchi for a long period of time. Litchi orchards are concentrated in southern China. In particular, the areas used for litchi cultivation in 2016 in Guangdong, Guangxi, Hainan, and Fujian covered 274080, 204340, 20980, and 27900 ha, respectively. The outputs from those four provinces in order were 1246276, 667478, 153533, and 181614 tons. The findings of this study can provide evidence on the role of IES in farmers' fertilizer management ability. It can also serve as a reference for sustainable litchi production in China and other litchi-producing countries, such as India, Vietnam, Thailand, and Australia.

The remaining contents are organized as follows. Section 2 presents the theoretical construct. Section 3 provides an overview of the materials and methods. Empirical results are presented and discussed in Section 4. The final section is the conclusion.

## 2. Theoretical construct

The lack of proper nutrition management is one of the restricting factors of litchi production (Chen and Huang, 2014). Farmers' decisions on fertilizer use usually depend on the age of the litchi tree, the fruit load, and the size of the canopy. To promote sustainable development of the litchi industry, the National Litchi and Longan Industry Technology System (NLLITS) was established in 2009. NLLITS has established litchi orchards to pilot and promote advanced production technology and sustainable orchard management practices. NLLITS also applied multiple ICT-based channels (e.g., web portal, online community, and smartphone apps) to disseminate free information on market price, fertilizer use, and pest control to farmers. According to the IES offered by NLLITS, the recommended ratio of N, P and K fertilizers is 1:0.4:0.94. The optimal use of N, P and K fertilizers recommended for trees bearing 50 kg of litchi is 1.47 kg, 0.35 kg, and 1.38 kg, respectively. Moreover, planting litchi too close together can impact their growth and fruit harvest. NLLITS recommends that farmers grow 42–74 litchi trees for every 1 mu of orchard. In this regard, the recommended chemical fertilizer use intensity is 134.4–236.8 kg/mu.

Even though conventional extension services have proven to be effective in promoting the correct use of fertilizer, agricultural

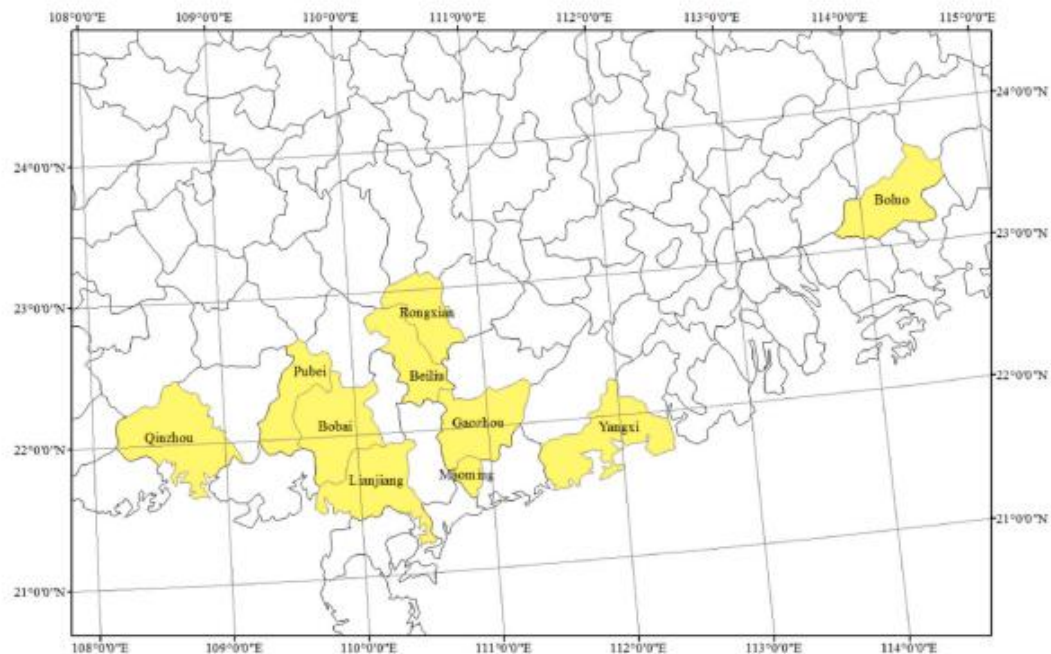


Fig. 1. Survey areas.

training can hardly cover all litchi growers due to limited budgets. The use of IES may help NLLITS extension workers reach out to smallholders at low cost. Another distinctive advantage of IES is that they allow users to customize agricultural extension services. IES users can easily access blanket advice online. They are also able to send pictures and make video calls to NLLITS extension workers for personalized advice. With the use of smartphones, they can also read fertilization guidelines and watch videos repeatedly.

### 3. Materials and methods

#### 3.1. Data collection

This study used litchi production survey data for empirical analysis. The survey was conducted in August 2018 by the NLLITS survey team. The team used a sampling method of stratified probability proportional to the area used for data collection. In particular, the survey covers litchi-producing counties, including Qinzhou, Pubei, Bolai, Rongxian, and Beiliu in Guangxi Province and Lianjiang, Maoming, Gaozhou, Boluo, and Yangxi in Guangdong Province (see Fig. 1). Towns in the selected areas were divided into large, medium, and small categories based on the litchi cultivation area. We randomly selected 1 large and 1 medium litchi-producing town from each county. Following the same rules, 2 litchi-producing villages were selected from each town. Finally, approximately 20–25 sample farmers were randomly selected from each village. After dropping households that do not participate in litchi production, the research team collected 828 observations (see Appendix Table 1 for sample distribution).

The team developed a structured questionnaire that contains several blocks of questions. During face-to-face interviews, information on household characteristics, litchi input and output, fertilizer knowledge, IES use, and asset ownership was collected.

#### 3.2. Measurement of variables

Table 1 presents the definitions and descriptive statistics of the variables used in this study. With regard to litchi production, the average litchi output per household is 15018.63 kg/ha. Fertilizer is measured by the quantity of chemical fertilizer used. Labor is the sum of days of family labor and hired labor. Capital input is the material cost (e.g., for irrigation, machines, manure) except for the cost of the chemical fertilizer. On average, farmers own 1.06 ha of litchi orchards, use 739.411 kg of fertilizer, work for 12.589 days, and spend 40189.996 yuan on 1 ha of litchi orchards.

**Table 1**  
Definition and descriptive statistics of variables.

| Variables                 | Definition                                                                                                                                                                                                                    | Mean (S.D.)               |
|---------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------|
| Litchi output             | Litchi total output (kg/ha)                                                                                                                                                                                                   | 15018.630<br>(23305.574)  |
| Fertilizer                | Chemical fertilizer input (kg/ha)                                                                                                                                                                                             | 739.41 (1461.213)         |
| Labor                     | Labor input (days/ha)                                                                                                                                                                                                         | 12.589 (19.775)           |
| Land                      | The size of the litchi orchard (ha)                                                                                                                                                                                           | 1.06 (1.240)              |
| Capital                   | Material cost (e.g., irrigation, machines, manure) except for the cost of the chemical fertilizer (yuan/ha)                                                                                                                   | 40189.996<br>(110914.427) |
| IES use                   | 1 = ICT-based extension service user; 0 = nonuser                                                                                                                                                                             | 0.401 (0.490)             |
| Effectiveness             | Knowledge about the effects of fertilizer at litchi planting, flower-bud differentiating, flower-bearing, fruit-bearing, and after-harvest stages: 1 = poor; 2 = fair; 3 = good; 4 = very good; 5 = excellent                 | 3.033 (1.189)             |
| Procedural                | Knowledge about how to use fertilizer in an effective way at litchi planting, flower-bud differentiating, flower-bearing, fruit-bearing, and after-harvest stages: 1 = poor; 2 = fair; 3 = good; 4 = very good; 5 = excellent | 3.159 (1.197)             |
| Declarative               | Knowledge about the way nutrition works at litchi planting, flower-bud differentiating, flower-bearing, fruit-bearing, and after-harvest stages: 1 = poor; 2 = fair; 3 = good; 4 = very good; 5 = excellent                   | 2.816 (1.259)             |
| Technical efficiency      | The relationship between farm input and output, estimated by authors                                                                                                                                                          | 0.544 (0.196)             |
| Fertilizer use efficiency | The ratio of optimal quantity of fertilizer use to actual use, estimated by authors                                                                                                                                           | 0.533 (0.124)             |
| Gender                    | 1 = male, 0 = otherwise                                                                                                                                                                                                       | 0.888 (0.316)             |
| Age                       | Age of the household head                                                                                                                                                                                                     | 56.814 (10.799)           |
| Education                 | Number of school years                                                                                                                                                                                                        | 8.358 (2.973)             |
| Health                    | 3 = good, 2 = average, 1 = bad                                                                                                                                                                                                | 2.737 (0.506)             |
| Off-farm work             | 1 = yes, 0 = otherwise                                                                                                                                                                                                        | 0.181 (0.385)             |
| Farming experience        | Years of farming                                                                                                                                                                                                              | 22.560 (9.728)            |
| Training participation    | 1 = yes, 0 = otherwise                                                                                                                                                                                                        | 0.579 (0.494)             |
| Household income          | 2017 household income (10,000 Yuan)                                                                                                                                                                                           | 9.701 (16.284)            |
| Share of litchi income    | Litchi income in the proportion of total household income                                                                                                                                                                     | 40.595 (34.831)           |
| CPC membership            | 1 = yes, 0 = otherwise                                                                                                                                                                                                        | 0.225 (0.418)             |
| Cooperative membership    | 1 = yes, 0 = otherwise                                                                                                                                                                                                        | 0.287 (0.453)             |
| Family member             | The number of household members whose age is between 16 and 65                                                                                                                                                                | 3.942 (1.797)             |
| Land                      | The size of the litchi orchard (ha)                                                                                                                                                                                           | 1.060 (2.395)             |
| Fertilization brochure    | Do you have a litchi production fertilization brochure?                                                                                                                                                                       | 0.215 (0.411)             |
|                           | 1 = yes, 0 = otherwise                                                                                                                                                                                                        |                           |

Regarding the variable of interest, the value of IES use takes 1 if a farmer adopts IES. The outcome variables include fertilizer knowledge and use efficiency. Previous studies suggest that effectiveness and both procedural and declarative knowledge may affect farmers' ecological behaviors (Kaiser and Fuhrer, 2003; Redman and Redman, 2014). Existing research reveals that Chinese farmers have an insufficient understanding of the effects of fertilizer, how to use fertilizer effectively, and the way nutrition works (Huang et al., 2008; Pan and Zhang, 2018). In this study, the scores of fertilizer effectiveness and procedural and declarative knowledge are related to farmers' understanding of the effects of fertilizer, how to use fertilizer effectively, and the way nutrition works at the different stages of litchi planting, flower-bud differentiating, flower bearing, fruit bearing, and after harvesting. These scores are self-reported and range from 0 to 5. The technical and fertilizer use efficiency scores are estimated using the stochastic frontier production (SFP) model mentioned in Section 3.3.

In terms of household characteristics, 88.8% of household heads are male. Household heads are 56.8 years old on average and received 8.4 years of education. The result suggests that 18.1% of surveyed households have participated in off-farm work. Approximately 22.5% and 28.7% of households have CPC membership and cooperative membership, respectively.

### 3.3. Statistical model specification

Following Wu (2011) and Bai et al. (2019), this study employs the stochastic frontier production (SFP) model to estimate fertilizer use efficiency. We assume  $Y$  is litchi output and there are four inputs, including labor ( $L$ ), land ( $D$ ), capital ( $C$ ), and fertilizer ( $F$ ). The model can be expressed as:

$$\ln Y = \ln f(L, D, C, F; \beta) + v - u \quad (1)$$

where  $\beta$  is a vector of parameters to be estimated;  $v$  is a random error and  $v \sim iid(0, \sigma_v^2)$ ; and  $u$  captures the inefficiency effect in the production process and is assumed to be nonnegative and distributed independently.

Technical efficiency ( $TE$ ) is defined as  $TE = e^{-u}$  (Battese and Coelli, 1995). Fertilizer use efficiency ( $FE$ ) is defined as the ratio of the minimum required quantity of fertilizer ( $F^{min}$ ) to the observed quantity of fertilizer ( $F$ ), which can be expressed as follows:

$$FE = \min\{\theta : (L, D, C, F^{min}) = (L, D, C, \theta F) \text{ can produce } Y\} \leq 1 \quad (2)$$

where  $\theta$  denotes the ratio of the minimum fertilizer input to the observed quantity of fertilizer.

Technical efficiency can be achieved only when there is no  $TE$  loss in the production process. This suggests that  $u_i = 0$  and  $F = F^{min}$ . In this case, the production function can be expressed as follows:

$$\ln Y = \ln f(L, D, C, \theta F; \beta) + v \quad (3)$$

We use the translog production function to estimate  $TE$  and  $FE$ . For litchi farm household  $i$ , the function can be specified as follows:

Table 2  
Results of the stochastic frontier function model.

| Variable                   | Coefficient | SE    |
|----------------------------|-------------|-------|
| $\ln L (\beta_1)$          | -0.0124     | 0.030 |
| $\ln D (\beta_2)$          | 0.480***    | 0.093 |
| $\ln C (\beta_3)$          | 0.0452**    | 0.020 |
| $\ln F (\beta_4)$          | 0.079***    | 0.028 |
| $\ln L \ln D (\beta_{12})$ | -0.004      | 0.007 |
| $\ln L \ln C (\beta_{13})$ | 0.004*      | 0.003 |
| $\ln L \ln F (\beta_{14})$ | -0.003      | 0.002 |
| $\ln D \ln C (\beta_{23})$ | 0.015       | 0.010 |
| $\ln D \ln F (\beta_{24})$ | 0.009       | 0.011 |
| $\ln C \ln F (\beta_{34})$ | -0.010***   | 0.003 |
| $\ln^2 L (\beta_{11})$     | -0.001      | 0.004 |
| $\ln^2 D (\beta_{22})$     | -0.021      | 0.023 |
| $\ln^2 C (\beta_{33})$     | 0.007***    | 0.002 |
| $\ln^2 F (\beta_{44})$     | 0.006**     | 0.002 |
| Constant                   | 7.575***    | 0.257 |
| $\lambda$                  | 1.278***    | 0.075 |
| $\sigma$                   | 1.076***    |       |
| Log likelihood             | -1188.086   |       |
| LR test                    | 47.32***    |       |
| Sample size                | 828         |       |

Note: (i) \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.  
(ii)  $\lambda = \sigma_u/\sigma_v$  and  $\sigma^2 = \sigma_v^2 + \sigma_u^2$ , where  $\sigma_v^2$  is defined in Equation (1) and  $\sigma_u^2$  is the variance of  $u$  in Equation (4).

$$\ln Y_i = \beta_0 + \beta_1 \ln L_i + \beta_2 \ln D_i + \beta_3 \ln C_i + \beta_4 \ln F_i + \beta_{12} \ln L_i \ln D_i + \beta_{13} \ln L_i \ln C_i + \beta_{14} \ln L_i \ln F_i + \beta_{23} \ln D_i \ln C_i + \beta_{24} \ln D_i \ln F_i + \beta_{34} \ln C_i \ln F_i + \beta_{11} \ln^2 L_i + \beta_{22} \ln^2 D_i + \beta_{33} \ln^2 C_i + \beta_{44} \ln^2 F_i + v_i - u_i \quad (4)$$

Subsequently,  $FE$  can be obtained using Equation (5):

$$FE_i = \exp \left\{ \frac{-\zeta_i \pm \sqrt{\zeta_i^2 - 4\beta_{44}u_i}}{2\beta_{44}} \right\} \quad (5)$$

where  $\zeta_i = \beta_4 + \beta_{14} \ln L_i + \beta_{24} \ln D_i + \beta_{34} \ln C_i + 2\beta_{44} \ln F_i$ .

Existing research suggests that a farmer's decision regarding IES use is not random (Fu and Akter, 2016; Kiiza and Pederson, 2012; Larochelle et al., 2019; Ogutu et al., 2014). We divide the sampled farmers into treatment and control groups and present information regarding the mean differences between IES users and nonusers in Appendix Table 2. The mean-comparison test indicates that farmers who adopt the IES differ significantly from nonusers regarding age, education, health, off-farm work, farming experience, training participation, household income, CPC membership, cooperative membership, land, and fertilization brochure. These results suggest the potential existence of self-selection bias.

To reduce selection bias arising from observables, some previous studies, such as Kiiza and Pederson (2012) and Ogutu et al. (2014), adopted the PSM technique for empirical analysis. However, one critical assumption for achieving consistent and unbiased estimated results in the PSM approach is the correct specification of the treatment model. In this study, we employed an inverse probability weighted adjusted regression (IPWRA) model for empirical analysis. The IPWRA estimator has a doubly robust property (Linden et al., 2016; Uysal, 2015). It can provide an unbiased evaluation when the treatment or outcome model is correctly specified.

The IPWRA model includes both treatment and outcome models. We considered farmers' decisions on IES use under a random utility framework in the treatment model. Farmer  $i$  will adopt IES use when the utility ( $U_{IU}$ ) is higher than that of not using IES ( $U_{IN}$ ). However, in an observational study, the utility difference ( $T_i^* = U_{IU} - U_{IN}$ ) that drives farmers' decision-making is not observable. We can collect only information that represents farmers' IES use status ( $T_i$ ). Alternatively, this can be expressed as follows:

$$T_i^*(x_i) = \frac{\exp(x_i \beta_i)}{1 + \exp(x_i \beta_i)} \text{ with } T_i = \begin{cases} 1 & \text{if } T_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where  $T_i^*$  is the utility difference between using the IES and not using it.  $T_i = 1$  if a farmer  $i$  uses the IES and  $T_i = 0$  otherwise.  $x_i$  is a vector of variables that influence the farmer's decision-making on IES use.

IES use is expected to improve fertilizer knowledge and use efficiency. Therefore, the outcome model can be expressed as follows:

$$R_i = \alpha_i + \theta_i x_i + e_i \quad (7)$$

where  $R_i$  is the outcome variable,  $x_i$  is a set of control variables,  $\alpha_i$  is a constant,  $\theta_i$  is a parameter to be estimated, and  $e_i$  is the error term.

After estimating the propensity scores in the treatment model and the inverse probability weighted parameters in the outcome model, the average treatment effect on the treated (ATT) can be estimated as follows (Linden et al., 2016; Uysal, 2015):

$$ATT = \frac{1}{N_1} \sum_{i=1}^{N_1} [(\hat{\alpha}_1 - \hat{\alpha}_0) - (\hat{\theta}_1 - \hat{\theta}_0)] \quad (8)$$

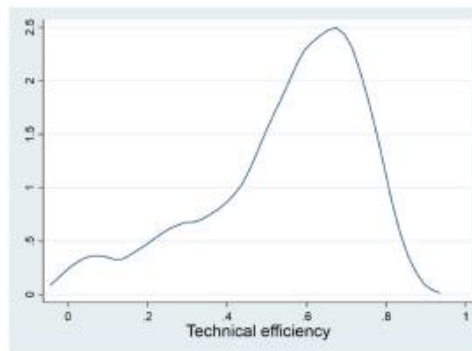


Fig. 2. Kernel density distribution of technical efficiency.

where  $N$  and  $N_1$  represent the whole sample and the treatment group, respectively, and  $(\hat{\alpha}_1, \hat{\theta}_1)$  and  $(\hat{\alpha}_0, \hat{\theta}_0)$  are the estimated inverse probability weighted parameters for the treatment group and control group, respectively.

#### 4. Results and discussion

##### 4.1. Fertilizer use efficiency estimation

We used Stata 14.0 to analyze the data. The results of the SFP model are shown in Table 2. The LR test result shows that the stochastic frontier function is preferred to the standard translog function. The value of  $\lambda$  indicates that a large part of the residual is due to the inefficiency component.

The kernel density distributions of the estimated technical and fertilizer use efficiencies are presented in Figs. 2 and 3. The mean of technical efficiency is 0.544, and the distribution is skewed toward the right. The fertilizer use efficiency score ranged from 0.170 to 0.984, with a mean value of 0.533. These results suggest inefficient production and fertilizer management among litchi growers. Our finding is in line with that of previous research. For example, a previous study reports that the fertilizer use efficiency among crop producers in rural China is 0.333 (Wu, 2011). Another study on rice farmers provides a similar result ( $FE = 0.254$ ) (L. Ma et al., 2014). A recent study found that the fertilizer use efficiency of Chinese apple farmers is 0.472 (Bai et al., 2019).

Moreover, the technical and fertilizer use efficiencies for IES users are 0.564 and 0.538, respectively. The figures for nonusers are 0.532 and 0.528. The differences between IES users and nonusers are significant (see Appendix Table 2).

##### 4.2. Determinants of IES use

We used a logit model to estimate the propensity scores and present the results in Table 3. In addition to the coefficients of the variables, marginal effects are also provided to facilitate discussion. The results suggest that IES use is affected by age, education, off-farm work, training, family member, and CPC membership. In particular, our results indicate that the younger generation is more likely to adopt IES. This finding is in line with previous research on farmers' ICT usage patterns (Goldfarb and Prince, 2008). The coefficient of education is positive and statistically significant. This result indicates that education improves farmers' ability to use IESs. This is in line with existing research on ICT adoption (Khanal and Mishra, 2016; Ogutu et al., 2014). Moreover, off-farm work and training increase the probability of IES adoption by 6.1% and 9.7%, respectively. The peer effects of off-farm work and training participation may raise farmers' awareness of IES.

##### 4.3. Treatment effects estimation

Table 4 shows the treatment effects of IES use on fertilizer knowledge and use efficiency. We found that IES use has positive and statistically significant impacts on fertilizer knowledge and use efficiency. In particular, the estimated ATTs for fertilizer effectiveness, procedural, and declarative knowledge are 0.233, 0.230 and 0.149, respectively. The figures for technical and fertilizer use efficiency are 0.066 and 0.021, respectively. These coefficients are significant at the 10% or higher significance level. The results indicate that the fertilizer effectiveness, procedural and declarative knowledge will be increased by 7.22%, 6.91%, and 4.95%, respectively, because of IES use. Moreover, IES users' technical and fertilizer use efficiency will be increased by 13.35% and 4.15%, respectively.

For comparison and robustness checks, the estimated ATTs using PSM (one-to-one matching) are also presented in Table 4. These results confirm the positive role of IES use in improving fertilizer knowledge and use efficiency.

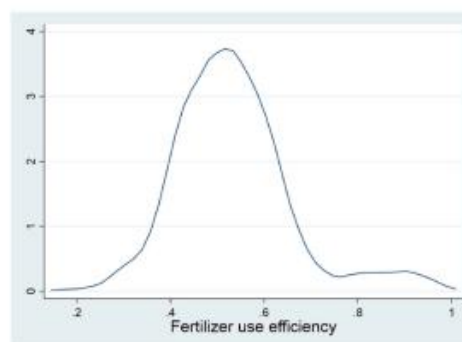


Fig. 3. Kernel density distribution of fertilizer use efficiency.

**Table 3**  
Propensity score estimation results.

| Variable               | IES use           |                  |
|------------------------|-------------------|------------------|
|                        | Coefficients      | Marginal effects |
| Gender                 | 0.067 (0.303)     | 0.022            |
| Age                    | -0.180 (0.015)*** | -0.024***        |
| Education              | 0.210 (0.041)***  | 0.028***         |
| Health                 | -0.222 (0.206)    | -0.029           |
| Off-farm work          | 0.476 (0.253)*    | 0.062*           |
| Farming experience     | 0.008 (0.012)     | 0.001            |
| Training               | 0.792 (0.224)***  | 0.104***         |
| Household income       | 0.006 (0.010)     | 0.001            |
| Share of litchi income | -0.001 (0.003)    | 0.000            |
| CPC membership         | 0.625 (0.237)***  | 0.082***         |
| Cooperative membership | -0.135 (0.231)    | -0.017           |
| Family member          | 0.108 (0.061)*    | 0.014*           |
| Farm size              | 0.007 (0.004)     | 0.001            |
| Fertilization brochure | 0.236 (0.240)     | 0.031            |
| Location dummies       | Controlled        |                  |
| Observations           | 828               | 828              |

Note: (i) The reference region is Zhanjiang City; (ii) standard errors in parentheses; (iii) \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 4**  
ATT estimation of IES use.

|                           | IPWRA            |        | PSM              |
|---------------------------|------------------|--------|------------------|
|                           | Coef. (S.E.)     | PCT    | Coef. (S.E.)     |
| Effectiveness knowledge   | 0.233* (0.127)   | 7.22%  | 0.336*** (0.080) |
| Procedural knowledge      | 0.230** (0.116)  | 6.91%  | 0.293*** (0.081) |
| Declarative knowledge     | 0.149* (0.135)   | 4.95%  | 0.315*** (0.085) |
| Technical efficiency      | 0.066*** (0.021) | 13.35% | 0.064*** (0.029) |
| Fertilizer use efficiency | 0.021* (0.014)   | 4.15%  | 0.015* (0.019)   |

Note: (i) \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively. (ii) The one-to-one matching PSM technique is applied in ATT estimation.

#### 4.4. Discussion

Unlike previous studies, this study focuses on the effects of IES use on fertilizer knowledge and use efficiency rather than the intensity of fertilizer use. Our results indicate that IES use improves the fertilizer managerial ability of farmers. The finding that IES use has a positive effect on farmers' fertilizer knowledge is supported by Fu and Akter (2016) and Larochelle et al. (2019). The improvement in fertilizer knowledge that is related to IES use could be related to the reduction in the delivery cost of extension services. NLLITS extension workers use the internet to promote the correct use of fertilizer. There is a rich body of online information regarding the effects of fertilizer, how to use fertilizer, and the way nutrition works at different stages of litchi production. Internet and smartphone users can access fertilizer management knowledge from various sources, including extension workers, online training classes, and smartphone apps. The improvement in fertilizer knowledge leads to an increase in fertilizer use efficiency.

China faces enormous challenges in achieving zero growth in fertilizer use. Our findings imply that IES use has positive impact on fertilizer management. From a policy perspective, the needs for improving IES adoption and access to ICT-based fertilizer management content are brought to the fore. Given that farmers who are training are more likely to use IES, governments can encourage farmers to participate in training and offer more ICT-related training sessions. Moreover, both public and private sector actors should create more online content regarding the correct use of fertilizer and develop smartphone apps for fertilizer management.

#### 5. Conclusions

This paper evaluates the treatment effects of IES use on litchi growers' fertilizer knowledge and use efficiency by employing the IPWRA model. The empirical results suggest that IES use has positive effects on fertilizer knowledge and use efficiency. Our findings imply that IES is a promising tool to improve fertilizer management.

This study is limited by the fact that we used self-reported information to estimate fertilizer knowledge. Moreover, land ownership may affect farmers' adoption of practices. We did not collect information on land ownership through this survey. It is suggested that future studies validate farmers' fertilizer knowledge via their fertilization behavior and control for the variable of land ownership. In addition, site-specific fertilizer management is becoming available to farmers and has the potential to further improve fertilizer use efficiency. Future research should pay more attention to the adoption of such digital innovations for fertilizer management.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

### Acknowledgements

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### Appendix

**Table 1**  
Sample distribution

| Province  | County/District | Sample size | Percent |
|-----------|-----------------|-------------|---------|
| Guangxi   | Beiliu          | 82          | 9.9%    |
|           | Rongxian        | 84          | 10.1%   |
|           | Qinzhou         | 79          | 9.5%    |
|           | Pubei           | 94          | 11.4%   |
|           | Bobai           | 90          | 10.7%   |
| Guangdong | Gaozhou         | 85          | 10.3%   |
|           | Maoming         | 82          | 9.9%    |
|           | Boluo           | 55          | 6.6%    |
|           | Lianjiang       | 73          | 8.8%    |
|           | Yangxi          | 104         | 12.6%   |

**Table 2**  
Mean differences between IES users and nonusers

| Variable                  | IES users       | IES nonusers    | Difference in mean |
|---------------------------|-----------------|-----------------|--------------------|
| Effectiveness knowledge   | 3.246 (1.140)   | 2.889 (1.201)   | 0.357***           |
| Procedural knowledge      | 3.348 (1.135)   | 3.032 (1.222)   | 0.316***           |
| Declarative knowledge     | 3.018 (1.257)   | 2.680 (1.243)   | 0.337***           |
| Technical efficiency      | 0.564 (0.205)   | 0.532 (0.182)   | 0.325**            |
| Fertilizer use efficiency | 0.538 (0.121)   | 0.528 (0.127)   | 0.010*             |
| Gender                    | 0.871 (0.336)   | 0.899 (0.302)   | 0.028              |
| Age                       | 49.375 (9.029)  | 61.818 (8.833)  | -12.443***         |
| Education                 | 9.486 (2.439)   | 7.600 (3.062)   | -1.886***          |
| Health                    | 2.838 (0.422)   | 2.670 (0.546)   | 0.167***           |
| Off-farm work             | 0.288 (0.453)   | 0.109 (0.312)   | 0.179***           |
| Farming experience        | 20.850 (9.086)  | 23.711 (9.982)  | -2.861***          |
| Training                  | 0.670 (0.471)   | 0.517 (0.500)   | 0.152***           |
| Household income          | 11.464 (21.494) | 8.515 (11.398)  | 2.949**            |
| Share of litchi income    | 40.406 (34.029) | 40.722 (35.394) | -0.316             |
| CPC membership            | 0.300 (0.459)   | 0.173 (0.379)   | 0.127***           |
| Cooperative membership    | 0.321 (0.468)   | 0.264 (0.442)   | 0.056*             |
| Labor                     | 3.984 (1.589)   | 3.913 (1.953)   | -0.072             |
| Land                      | 1.464 (3.360)   | 0.789 (1.356)   | 0.674***           |
| Fertilization brochure    | 0.252 (0.435)   | 0.189 (0.393)   | 0.062*             |
| Sample size               | 332             | 496             |                    |

Note: (i) \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

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## 2. 2. Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China

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# Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China

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## Abstract

This study uses a dataset covering 928 small litchi growers in southern China to investigate the determinants of farmers' willingness to adopt digital pest and disease management (DPDM), focusing on smartphone use. An endogenous switching probit model is employed to address potential selection bias. The result confirms the positive role of smartphone use on willingness to adopt DPDM. Age, education, health, wealth, cooperative membership, and credit access are also associated with farmers' willingness to adopt DPDM. Moreover, we find that the determinants of smartphone users' and nonusers' willingness to adopt DPDM are different. Finally, we propose a digital inclusion agenda to promote rural smartphone adoption and use in agriculture. [EconLit Citations: Q16, Q18].

## KEYWORDS

digital pest and disease management, litchi grower, rural China, smartphone use, willingness to adopt

## 1 | INTRODUCTION

Pest and disease outbreaks threaten the sustainable development of agriculture and the livelihood of smallholder farmers (FAO, 2021). Early intervention is essential to prevent pest and disease outbreaks. However, it is also a major challenge in the agricultural field. The ongoing digital revolution provides a solution for this problem. Digital

**Abbreviations:** ATT, average treatment effect on the treated; ATU, average treatment effect on the untreated; CPC, Communist Party of China; DPDM, digital pest and disease management; ERM, extended regression model; ESP, endogenous switching probit model; GPS, the global positioning system; ICT, information and communication technology; IV, instrumental variable; NGO, Non-governmental organization; TH, transitional heterogeneity; TT, treatment effect on the treated; TU, treatment effect on the untreated.

pest and disease management (DPDM) is able to increase farmers' field scouting efficiency. It uses sensors to monitor crop growth and to identify pests and diseases. Tailored recommendations can thus be generated by combining individual- and macro-level data to support farmers' decision-making processes (Deepthi & Sreekantha, 2017; Johannes et al., 2017; Lucas, 2011; Panda, 2020; Wang et al., 2013). Despite government efforts to promote digital agriculture innovations (e.g., DPDM), smallholder farmers in developing countries continue to struggle with recognizing the value of digital technology and adoption (Lowenberg-DeBoer & Erickson, 2019).

Over the past decade, farmers in developing countries have gradually adopted smartphones and benefited from the use of this modern information and communication (ICT) tool (Ma, Grafton, et al., 2020; Ma, Renwick, et al., 2018; Nie et al., 2020; Rajkhowa & Qaim, 2022; Zheng & Ma, 2021). Smartphone use generates immediate private benefits as it expands information sources and reduces search costs. Evidence from rural China and India suggests that smartphone use increases both farm household income and farmer's subjective well-being (Ma, Grafton, et al., 2018; Ma, Renwick, et al., 2018; Nie et al., 2020; Rajkhowa & Qaim, 2022). Another distinct advantage of smartphone is that it enables users to customize education and agricultural extension services. For example, Zheng and Ma (2021) find that Chinese wheat growers improve crop yields, net income, and return on investment after using smartphones. Moreover, smartphones can serve as the infrastructure of digital agriculture innovations (Pongnumkul et al., 2015). Recently, governments, NGOs, and donors have developed smartphone-based applications (apps) for farm management for smallholder farmers (Campenhout, 2017; Cole & Fernando, 2021; Satyanarayan et al., 2018). Given these advantages of smartphone use, understanding the relationship between smartphone use and willingness to adopt DPDM could provide references for controlling pests and diseases, preventing crop loss, and reducing pesticide use.

This study contributes to the literature by investigating the effects of smartphone use on farmers' willingness to adopt DPDM. Although there is evidence that mobile phone- and Internet-using farmers are more likely to adopt integrated pest management techniques (Ma & Wang, 2020) and reduce pesticide use (Zhao et al., 2021), less is known about the effect of smartphone use on farmer's willingness to adopt the digital solution for pest and disease management. The use of DPDM may further increase the efficiency and effectiveness of pest and disease control and reduce pesticide use because it is able to detect and solve the problem at the early stage.

We use a dataset covering 928 smallholder litchi farmers from southern China. China is an ideal setting because the transformation toward digital agriculture is a government priority (Zhang et al., 2016). In late 2019, China unveiled its 2019–2025 rural and agricultural digitization development plan. The plan seeks to leverage digital innovations to find a path to sustainable intensive agriculture. Moreover, China is the largest litchi-producing country in the world (FAO, 2002). The Chinese litchi sector is dominated by smallholder farmers and is greatly affected by pests and diseases (e.g., downy mildew, anthracnose, fruit cracking, stink bugs, stem-end borer, and gall mite). Farmers scout orchards and try to identify pests and diseases based on their personal knowledge. Chemical pesticides are widely adopted by litchi growers to control pests and diseases. The extensive use of chemical pesticides not only costs farmers considerable money but also causes severe health and environmental issues (Möhring et al., 2020). DPDM adoption has the potential to detect pests and diseases at the early stage, and thus prevent crop loss and reduce pesticide use.

An endogenous switching probit model (ESP) is employed to address the problem of endogeneity. The model is able to investigate the determinants of farmers' smartphone use and the factors that influence their willingness to adopt DPDM for smartphone users and nonusers separately. It can also estimate consistent treatment effects of smartphone use on willingness to adopt DPDM by considering both observed and unobserved heterogeneities (Lokshin & Sajaia, 2011; Ma, Renwick, et al., 2018).

The rest of this study is organized as follows. Section 2 is the literature review. Section 3 outlines the conceptual framework and estimation strategy. Data and descriptive statistics are presented in Section 4. The results are presented and discussed in Section 5. Conclusions are drawn in the final section.

## 2 | LITERATURE REVIEW

### 2.1 | Impact of ICT use on smallholder farmers

In developing countries, the number of rural ICT (e.g., Internet and smartphone) users has continued to grow due to the introduction of low-cost smart devices and the expansion of mobile network coverage (WorldBank, 2016). The use of ICT can alleviate information asymmetry. There is a growing body of evidence suggesting that ICT adoption has a positive impact on the welfare of smallholder farmers (Aker, 2010; Aker & Ksoll, 2016; R. Jensen, 2007; R. T. Jensen, 2010; Min et al., 2020; Twumasi et al., 2021; Zhu et al., 2021). In particular, existing research finds that ICT use increases farmers' farm and nonfarm income. Evidence suggests that rural smartphone users have more opportunities to participate in off-farm work (Ma, Renwick, et al., 2018). ICT use also increases farmers' awareness and agricultural knowledge (Fu & Akter, 2016; Larochelle et al., 2019). Moreover, rural ICT users are found to be using more modern inputs, such as improved seeds, fertilizer, and pesticides (Campenhout, 2017; Campenhout et al., 2021; Cole & Fernando, 2021; Kiiza & Pederson, 2012; Ogutu et al., 2014). They also benefit from adopting more sustainable agricultural practices (Larochelle et al., 2019; Ma & Wang, 2020).

### 2.2 | Factors influencing farmer's adoption of digital agriculture innovation

Recently, farmers' adoption of digital agriculture innovation has received increasing attention. Evidence suggests that farmers' intention to adopt digital agriculture innovation is affected by household and farm characteristics (Annosi et al., 2019; Barnes et al., 2019; Hansen, 2015; H. G. Jensen et al., 2012; Kernecker et al., 2020; Pierpaoli et al., 2013; Tey & Brindal, 2012). Digital agriculture innovation adoption required large capital investments. Farm size is the factor most frequently cited as influencing farmers' decisions about digital agriculture innovation adoption because digital farming participants may enjoy an economy of scale (Batte & Arnholt, 2003; Kutter et al., 2011). Smallholder farmers are also constrained by tight budgets. In this regard, compared with smallholder farmers, large commercial farmers are more likely to adopt digital farming (H. G. Jensen et al., 2012). In the context of developing countries, weak extension service systems hinder the diffusion of new technologies (Takahashi et al., 2019). The low adoption rate is also due to the fact that farmers lack field sensors and have low digital literacy (Tsan et al., 2019). A study in Brazil finds that the limiting factors to digital farming adoption include age, farm size, and receptivity to technology (Pivoto et al., 2019). Evidence from Taiwan suggests that farmers' intention to use digital farming technologies (such as IoT, big data, image recognition, and apps) is affected by age, education, ICT ownership, and knowledge about and attitudes toward digital innovation (Chuang, Wang, & Liang, 2020; Chuang, Wang, & Liou, 2020). Farmers' decision on digital agriculture innovation adoption is also affected by their social network (Busse et al., 2013).

## 3 | CONCEPTUAL FRAMEWORK AND ESTIMATION STRATEGY

### 3.1 | Conceptual framework

Farm size, risk exposure and capacity to bear risks, human capital, labor availability, credit constraint, tenure, and access to commodity markets are identified as the main factors that determine the agricultural innovation adoption by smallholder farmers in developing countries (Feder et al., 1985). Using digital farming innovations further requires infrastructure, digital literacy, and technical knowledge and skills (FAO, 2019). Smartphone use may increase farmers' willingness to adopt DPDM by providing infrastructure and access to extension service and improving farmers' digital literacy.

The smartphone is a well-functioning digital infrastructure. Some DPDM apps are designed to run on smartphones. Smartphone offers the possibility to install DPDM apps according to farmers' needs. Smartphone-based DPDM apps are capable of collecting raw data from the crop field using the smartphone's built-in sensors (e.g., camera and GPS) (Pongnumkul et al., 2015). After symptoms are matched with an online database, tailored recommendations will be offered (Hallau et al., 2018).

Using ICTs to deliver agriculture extension services has the potential to alleviate the cost and improve service coverage (Aker, 2011; Aker et al., 2016; Norton & Alwang, 2020). Nowadays, ICT-based extension service has been available for smallholder farmers in developing countries (Arouna et al., 2021; Larochelle et al., 2019; Zhang et al., 2016). Rural farmers can use the smartphone to collect information for farm management on the Internet. Accordingly, farmers' awareness and knowledge of digital agriculture innovations can be improved via the use of a smartphone (Fu & Akter, 2016). Moreover, smartphone users can exchange information and knowledge of pest and disease control with extension workers and fellow farmers. In particular, novice smartphone users can access DPDM by sending pictures and videos from their field scout to extension workers for inspection. In the meantime, farmers gain experience and build confidence in interactions with the smartphone. Evidence suggests that familiarity with digital technology is positively associated with digital farming adoption (Pivoto et al., 2019).

## 3.2 | Estimation strategy

### 3.2.1 | Selection bias issue and model selection

In examining the effects of farmers' smartphone use on willingness to adopt DPDM, we obtain biased results by simply attributing the differences in outcomes between the treatment group (i.e., smartphone users) and the control group (smartphone nonusers) to treatment. Previous research on ICT (e.g., Internet, smartphone) adoption suggests that farmers are not randomly assigned to ICT user and nonuser groups (Hübler & Hartje, 2016; Leng et al., 2020; Ma & Zhu, 2020; Mwololo et al., 2019). Moreover, some of the determinants of ICT adoption can be observed from field surveys (e.g., age, education, and training participation), while others cannot be observed (e.g., innate ability and personal preference) (Cui et al., 2016; Ma & Zhu, 2020).

The ESP model and extended regression model (ERM) are able to solve this problem (Lokshin & Sajaia, 2011; StataPress, 2019). These two models can consider both observed and unobserved characteristics in empirical analysis to address the problem of endogeneity. Using maximum likelihood estimation, ERM is able to measure the effect of an endogenous treatment assignment (StataPress, 2019). This method has been applied in the food sector (Jafari et al., 2022). Given our interest in investigating the factors that drive both smartphone users' and nonusers' willingness to adopt DPDM, the ESP model is preferred. Unlike the ERM model, the ESP model uses a switching equation to sort sampled farmers into smartphone user and nonuser groups. This approach allows us to investigate the determinants of willingness to adopt DPDM by smartphone users and nonusers separately (Lokshin & Sajaia, 2011).

### 3.2.2 | The ESP model

The decision to use smartphone and its impact on willingness to adopt DPDM can be modeled in a two-stage treatment framework with the ESP model. First, we model farmers' decisions on smartphone use with a random utility maximization framework. In this framework, farmer  $i$  will use a smartphone only when the utility he or she receives from smartphone adoption is greater than not using it. Using a discrete choice model, farmers' decisions on smartphone use can be expressed as follows:

$$T_i^* = \gamma_i Z_i + u_i, \begin{cases} T_i = 1 & \text{if } T_i^* > 0 \\ T_i = 0 & \text{if } T_i^* \leq 0 \end{cases} \quad (1)$$

where  $T_i^*$  is a latent variable of the farmer's propensity for smartphone use. The variable  $T_i$  is a dummy that takes 1 if the farmer is a smartphone user,  $Z_i$  is a vector of variables that determines the farmer's smartphone use,  $\gamma_i$  is a vector of parameters, and  $u_i$  is an error term.

Given that the farmer decides whether to use a smartphone, we model the smartphone user's propensity to adopt DPDM ( $y_{1i}^*$ ) as Equation (2a) in the second stage of the ESP model. Similarly, a nonuser's propensity to adopt DPDM ( $y_{0i}^*$ ) can be modeled as in Equation (2b):

$$y_{1i}^* = \beta_{1i} X_{1i} + \varepsilon_{1i}, \begin{cases} y_{1i} = 1 & \text{if } y_{1i}^* > 0 \\ y_{1i} = 0 & \text{if } y_{1i}^* \leq 0 \end{cases} \quad (2a)$$

$$y_{0i}^* = \beta_{0i} X_{0i} + \varepsilon_{0i}, \begin{cases} y_{0i} = 1 & \text{if } y_{0i}^* > 0 \\ y_{0i} = 0 & \text{if } y_{0i}^* \leq 0 \end{cases} \quad (2b)$$

where  $y_{1i}^*$  and  $y_{0i}^*$  are latent variables, and  $y_{1i}$  and  $y_{0i}$  are outcome variables. The variable  $y_{1i}$  takes the value of 1 if a smartphone user is willing to adopt DPDM and 0 otherwise. Variable  $y_{0i}$  takes the value of 1 if a smartphone nonuser is willing to adopt DPDM and 0 otherwise. Vectors  $X_{1i}$  and  $X_{0i}$  determine smartphone users' and nonusers' willingness to adopt DPDM (e.g., age, gender, cooperative membership, training participation, etc.),  $\beta_{1i}$  and  $\beta_{0i}$  are vectors of parameters, and  $\varepsilon_{1i}$  and  $\varepsilon_{0i}$  are error terms.

We use the `switch_probit` Stata command, which implements the maximum likelihood method to fit the model, to obtain consistent standard errors (Lokshin & Sajaia, 2011). Moreover, the ESP model uses an instrumental variable (IV) for model identification. A previous study used neighbors' internet use as an IV to estimate the effects of farmers' internet use on their willingness to adopt e-commerce (Ma et al., 2020). We thus include a variable that reflects neighbors' smartphone use. The IV equals 1 if a farmer's neighbor uses a smartphone. Moreover, we follow Ma, Renwick, et al. (2018) to test the IV's validity (Ma, Renwick, et al., 2018). In particular, we include neighbors' smartphone use variable in Equation (1), Equation (2a), and Equation (2b) and conduct the probit model for each equation separately. The results (see Table 4 for Equation [1] and Appendix Table A1 for Equations [2] and [3]) suggest that neighbors' smartphone use is significantly associated with farmers' smartphone use but not significantly related to the willingness to adopt DPDM.

Based on Equations (1), (2a), and (2b), we estimate the treatment effect on the treated (TT), that is, the effect of smartphone use on a smartphone user with observed characteristics  $x$  as follows (Aakvik et al., 2005; Lokshin & Sajaia, 2011):

$$TT = \Pr\{y_{1i}|T = 1, X = x\} - \Pr\{y_{0i}|T = 1, X = x\} = \frac{\phi_2(\beta_{1i} X_{1i}, \gamma_i Z_i, \rho_1) - \phi_2(\beta_{0i} X_{0i}, \gamma_i Z_i, \rho_0)}{F(\gamma_i Z_i)} \quad (3)$$

The treatment effect on the untreated (TU), that is, the effect of smartphone use on a smartphone nonuser with observed characteristics  $x$ , can be estimated as follows (Aakvik et al., 2005):

$$TU = \Pr\{y_{1i}|T = 0, X = x\} - \Pr\{y_{0i}|T = 0, X = x\} = \frac{\phi_2(\beta_{1i} X_{1i}, -\gamma_i Z_i, -\rho_1) - \phi_2(\beta_{0i} X_{0i}, -\gamma_i Z_i, -\rho_0)}{F(-\gamma_i Z_i)} \quad (4)$$

where  $\Pr\{y_{1i}|T = 1, X = x\}$  is the probability of a farmer who uses a smartphone and is willing to adopt DPDM. Probability  $\Pr\{y_{0i}|T = 1, X = x\}$  is the probability of a farmer who uses smartphone being unwilling to adopt DPDM. The probability  $\Pr\{y_{1i}|T = 0, X = x\}$  is for a farmer who does not use smartphone but is willing to adopt DPDM. The probability  $\Pr\{y_{0i}|T = 0, X = x\}$  is for a farmer who does not use smartphone and is unwilling to adopt DPDM. The cumulative function of a bivariate normal distribution is  $\phi_2$ ,  $F$  is a cumulative

TABLE 1 Relationship between treatment effects and heterogeneity effects

|                       | Willing to adopt                                            | Unwilling to adopt                                          | Treatment effect |
|-----------------------|-------------------------------------------------------------|-------------------------------------------------------------|------------------|
| Smartphone user       | $\frac{1}{N_U} \sum_{i=1}^{N_U} \Pr\{y_{1i} T = 1, X = x\}$ | $\frac{1}{N_U} \sum_{i=1}^{N_U} \Pr\{y_{0i} T = 1, X = x\}$ | ATT              |
| Smartphone nonuser    | $\frac{1}{N_N} \sum_{i=1}^{N_N} \Pr\{y_{1i} T = 0, X = x\}$ | $\frac{1}{N_N} \sum_{i=1}^{N_N} \Pr\{y_{0i} T = 0, X = x\}$ | ATU              |
| Heterogeneity effects | $BH_w$                                                      | $BH_{nw}$                                                   | TH               |

Abbreviations: ATT, average treatment effect on the treated; ATU, average treatment effect on the untreated; TH, transitional heterogeneity.

function of the univariate normal distribution,  $\rho_0$  is the correlation between  $\varepsilon_{0i}$  and  $u_i$ , and  $\rho_1$  is the correlation between  $\varepsilon_{1i}$  and  $u_i$ .

The average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) can then be estimated by averaging Equation (3) and Equation (4) over the observations in the smartphone user and nonuser groups (Lokshin & Sajaia, 2011):

$$ATT = \frac{1}{N_U} \sum_{i=1}^{N_U} \frac{\varphi_2(X_{1i}\beta_{1i}, ZY, \rho_1) - \varphi_2(X_{1i}\beta_{0i}, ZY, \rho_0)}{F(ZY)}, \quad (5)$$

$$ATU = \frac{1}{N_N} \sum_{i=1}^{N_N} \frac{\varphi_2(\beta_{1i}X_{1i}, -Y_iZ_i, -\rho_1) - \varphi_2(\beta_{0i}X_{0i}, -Y_iZ_i, -\rho_0)}{F(-Y_iZ_i)}, \quad (6)$$

where  $N_U$  is the number of farmers who use a smartphone ( $T = 1$ ) and  $N_N$  is the number of smartphone nonusers ( $T = 0$ ).

Farmers may have their own perceptions of digital innovations in the agriculture sector (Cui et al., 2016). Farmers who are aware of the benefit of digital innovations may inherently be willing to adopt DPDM regardless of their smartphone use. Accordingly, the base heterogeneity effect (BH) for the willingness to adopt DPDM group is (Carter & Milon, 2005):

$$BH_w = \frac{1}{N_U} \sum_{i=1}^{N_U} \Pr\{y_{1i}|T = 1, X = x\} - \frac{1}{N_N} \sum_{i=1}^{N_N} \Pr\{y_{1i}|T = 0, X = x\} \quad (7)$$

and that of the nonwilling to adopt DPDM group is:

$$BH_{nw} = \frac{1}{N_U} \sum_{i=1}^{N_U} \Pr\{y_{0i}|T = 1, X = x\} - \frac{1}{N_N} \sum_{i=1}^{N_N} \Pr\{y_{0i}|T = 0, X = x\}. \quad (8)$$

The transitional heterogeneity (TH) is the difference between ATT and ATU (see Table 1). TH refers to the difference between the treatment effects of smartphone use for smartphone users and nonusers.

## 4 | DATA AND DESCRIPTIVE STATISTICS

### 4.1 | Data collection

In August 2020, we conducted a survey of litchi growers in southern China. We first selected survey team members from South China Agricultural University. Graduate students who were familiar with the local language (Cantonese)

were preferred. Before the field survey, team members received training on data collection protocols (e.g., sampling procedures, questionnaire, team composition, deployment schedule) from leading experts. A structured questionnaire that contained several blocks of information, including demographic information, farming input, litchi sales, smartphone use, and willingness to adopt DPDM, was developed for data collection. Team members collected data through face-to-face interviews with the heads of households, that is, those responsible for agricultural decision-making.

Second, we used a multistage sampling method to collect household data. For location selection, the team first selected the provinces of Guangdong and Guangxi, as over 80% of China's total annual litchi production comes from these two regions. Second, the team selected the cities of Huizhou, Lianjiang, Maoming, and Yangjiang from Guangdong Province and Qinzhou and Yulin from Guangxi Province. Litchi production is concentrated in these six cities. Following the same rule, two litchi-producing counties were selected among Maoming, Yangjiang, Qinzhou, and Yulin, and one litchi-producing county was selected from Huizhou and Lianjiang. Fourth, two townships were randomly selected from each county. Fifth, we randomly picked two litchi-producing villages from each township. Finally, we randomly interviewed 25 farmers from each village.

The interviewers were separated into two teams to collect data from the Guangxi and Guangdong provinces during the same period. As a result, we interviewed 1000 farmers, with a nonresponse rate of 3%, for a final total of 970 households. After excluding households that did not participate in litchi production, we obtained a sample of 901 valid households.

## 4.2 | Variable definition and descriptive statistics

In this study, we are interested in the determinants of farmers' willingness to adopt DPDM, focusing on the role of smartphone use. Concerning the treatment variable, we collected information on farmers' smartphone use. The treatment variable equals 1 if the farmer is a smartphone user.

In terms of the outcome variable, we focus on farmers' willingness to adopt DPDM because of the extremely low DPDM adoption rate we found from the previous field surveys. During face-to-face interviews, we asked farmers whether they would like to adopt DPDM in the coming litchi production cycle. The outcome variable equals 1 if the farmer is willing to adopt DPDM.

Existing research suggests that farmers' decisions about Internet and smartphone use are determined by household head characteristics (e.g., age, gender, education, health) and farm characteristics (e.g., wealth, farm size, irrigation facilities) (Cole & Fernando, 2021; Fu & Akter, 2016; Hübner & Hartje, 2016; Leng et al., 2020; Ma & Zhu, 2020; Michels et al., 2020; Mwololo et al., 2019). For example, Ogutu et al. (2014) find that the number of crops, group membership, and farm size are positively associated with farmers' participation in ICT-based projects. They also find an inverse U-shaped effect of age on the likelihood of participation. Kiiza and Pederson (2012) find positive roles for loan access, farmer group membership, exposure to government awareness campaigns and negative roles for age, distance to trading center and district capital, and farm gate sales in determining farmers' use of ICT-based market information. Fu and Akter (2016) find that factors including age, gender, irrigation facilities, agricultural assets, and ICT ownership exert a significant impact on the speed and quality of mobile phone-based services reported by Indian farmers. Michels et al. (2020) identify age, education, and farm size as the determinants of farmers' smartphone adoption. Combined with the factors influencing farmer's adoption of digital agriculture innovation (see Section 2.2), we selected gender, age, education, health, training participation, farming year, labor, Communist Party of China (CPC) membership, cadre, wealth, farm size, cooperative membership, credit access, social network, and agriculture information service access as control variables. Age square is also included to capture the lifecycle effects. In addition, regional dummy variables are used to control for common regional effects.

Table 2 presents definitions and descriptive statistics for the variables used in this study. The results indicate that approximately 59% of the surveyed farmers use a smartphone. However, only 30.5% of farmers are willing to

TABLE 2 Variable definition and descriptive statistics

| Variable                               | Definition                                                                                                             | Mean (SD)       |
|----------------------------------------|------------------------------------------------------------------------------------------------------------------------|-----------------|
| Willingness to adopt                   | 1 = willing to adopt DPDM in the coming litchi production cycle, 0 = otherwise                                         | 0.305           |
| Smartphone use                         | 1 = smartphone user, 0 = otherwise                                                                                     | 0.592           |
| Gender                                 | 1 = male, 0 = female                                                                                                   | 0.862           |
| Age                                    | Household head's age in years                                                                                          | 57.521 (10.373) |
| Education                              | Years of household head's education                                                                                    | 8.585 (2.968)   |
| Health                                 | 1 = good, 0 = normal, -1 = bad                                                                                         | 0.721 (0.520)   |
| Training participation                 | 1 = household head participated in at least one agricultural training in the 2019–2020 production cycle, 0 = otherwise | 0.626           |
| Farm year                              | Household head farming experience in years                                                                             | 25.170 (10.418) |
| Labor                                  | Number of household members who are 16–65 years old                                                                    | 4.155 (1.597)   |
| CPC membership                         | 1 = at least one household member is a member of the Communist Party of China, 0 = otherwise                           | 0.291           |
| Cadre                                  | Number of household members who are village cadre                                                                      | 0.176 (0.446)   |
| Wealth                                 | Farmers' perception of the rank of their household wealth within the community, ranging from 1 to 5                    | 2.896 (0.775)   |
| Farm size                              | Litchi farming size (mu)                                                                                               | 18.522 (44.420) |
| Cooperative membership                 | 1 = cooperative member, 0 = otherwise                                                                                  | 0.349           |
| Credit access                          | Farmers' perception of easy access to credit, ranging from 1 to 5                                                      | 2.094 (1.201)   |
| Social network                         | The degree of cooperation among local farmers, ranging from 1 to 5                                                     | 3.181 (1.221)   |
| Agriculture information service access | 1 = having access to agriculture information service, 0 = otherwise                                                    | 0.418           |
| Guangxi                                | 1 = Guangxi farmer, 0 = otherwise                                                                                      | 0.494           |
| Guangdong                              | 1 = Guangdong farmer, 0 = otherwise                                                                                    | 0.506           |
| Neighbors' smartphone use              | 1 = farmer's neighbor uses smartphone, 0 = otherwise                                                                   | 0.923           |

Note: SDs for binary variables are not reported.

Abbreviation: CPC, Communist Party of China.

adopt DPDM. Most of the farmers are male (86.6%). The average farmer's age is 58 years. The average farmer has more than 8 years of schooling and 25 years of farming experience. A total of 62.6% of the surveyed household heads participated in the training. The means of the number of household members who are 16–65 years old and serve in cadres are 4.155 and 0.176, respectively. On average, sampled households cultivate 18.5 mu (1 mu = 0.067 hectare) of litchi. Approximately 30% of the surveyed households have at least one member of the CPC. In addition, around 35% of the sampled farmers had cooperative membership. 41.8% of farmers reported that they have access to agriculture information service. The dataset includes 49.4% Guangxi farmers and 50.6% Guangdong farmers.

We further split the sample based on farmers' smartphone use. Table 3 provides the mean difference comparison results between smartphone users and nonusers using the *t* test. The shares of willingness to adopt

DPDM for smartphone users and nonusers are 43.5% and 11.7%, respectively. The mean difference between the treatment and control groups was 31.8% points, and the figure was statistically significant at the 1% level. Moreover, significant differences in mean value were found between smartphone users and nonusers for several household head-, household- and farm-level characteristics. For example, farmers who adopt smartphones are younger and have better health and financial conditions than their counterparts. Smartphone users are better educated and also have a higher probability of participating in training and cooperative farming. A total of 34.1% of smartphone users have at least one CPC member within their families. The figure for nonusers is 21.7%. In addition, the average farm sizes of smartphone users and nonusers are 24.895 and 9.291 mu, respectively. Around 44% of smartphone users have access to agriculture information services. Only 38% of smartphone nonusers can receive agriculture information from extension workers. These results indicate the possible existence of selection bias in investigating the effects of farmers' smartphone use on their willingness to adopt DPDM.

## 5 | EMPIRICAL RESULTS

The ESP model results are presented in Tables 4 and 5. Specifically, the second column of Table 4 shows the first-stage results of the determinants of smartphone use. The last two columns of Table 4 show the determinants of willingness to adopt DPDM for smartphone users and nonusers. The treatment effects and heterogeneity effects of smartphone use on willingness to adopt DPDM are summarized in Table 5.

TABLE 3 Mean difference between smartphone users and nonusers

| Variables                              | Smartphone user | Smartphone nonuser | Mean difference |
|----------------------------------------|-----------------|--------------------|-----------------|
| Willingness to adopt                   | 0.435           | 0.117              | 0.318***        |
| Gender                                 | 0.846           | 0.878              | -0.032          |
| Age                                    | 53.259 (9.519)  | 63.834 (7.993)     | -10.575***      |
| Education                              | 9.342 (2.656)   | 7.489 (3.055)      | 1.853***        |
| Health                                 | 0.809 (0.443)   | 0.595 (0.592)      | 0.214***        |
| Training participation                 | 0.675           | 0.554              | 0.121***        |
| Farm year                              | 23.897 (10.545) | 27.015 (9.961)     | -3.118***       |
| Labor                                  | 4.128 (1.514)   | 4.196 (1.711)      | -0.068          |
| CPC membership                         | 0.341           | 0.217              | 0.124***        |
| Cadre                                  | 0.240 (0.512)   | 0.084 (0.306)      | 0.156***        |
| Wealth                                 | 2.983 (0.767)   | 2.769 (0.770)      | 0.214***        |
| Farm size                              | 24.895 (55.995) | 9.291 (12.213)     | 15.604***       |
| Cooperative membership                 | 0.398           | 0.277              | 0.121***        |
| Credit access                          | 2.139 (1.209)   | 2.030 (1.189)      | 0.108           |
| Social network                         | 3.191 (1.208)   | 3.166 (1.241)      | 0.026           |
| Agriculture information service access | 0.443           | 0.383              | 0.060*          |
| N                                      | 533             | 368                |                 |

Note: (i) Significance level: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . (ii) SD is presented in the parentheses. (iii) SDs for binary variables are not reported.

Abbreviation: CPC, Communist Party of China.

TABLE 4 ESP model results

| Variable                                        | Smartphone use          | Willingness to adopt DPDM |                |
|-------------------------------------------------|-------------------------|---------------------------|----------------|
|                                                 |                         | User                      | Nonuser        |
| Gender                                          | -0.179 (0.151)          | 0.163 (0.161)             | -0.261 (0.235) |
| Age                                             | -0.164** (0.079)        | -0.137** (0.057)          | 0.130 (0.163)  |
| Age square                                      | 0.001 (0.001)           | 0.001 (0.001)             | -0.001 (0.001) |
| Education                                       | 0.085*** (0.020)        | 0.037 (0.026)             | 0.019 (0.033)  |
| Health                                          | 0.179* (0.098)          | 0.199 (0.140)             | 0.289 (0.176)  |
| Training participation                          | 0.019 (0.117)           | -0.215 (0.134)            | 0.125 (0.196)  |
| Farm year                                       | 0.004 (0.006)           | 0.003 (-0.006)            | -0.001 (0.009) |
| Labor                                           | -0.039 (0.036)          | -0.036 (0.039)            | 0.053 (0.051)  |
| CPC membership                                  | 0.146 (0.089)           | 0.156 (0.098)             | -0.356 (0.200) |
| Cadre                                           | 0.427*** (0.142)        | 0.135 (0.127)             | 0.006 (0.259)  |
| Wealth                                          | 0.072 (0.073)           | 0.150* (0.083)            | 0.049 (0.123)  |
| Farm size                                       | 0.014*** (0.003)        | 0.000 (0.001)             | 0.004 (0.007)  |
| Cooperative membership                          | 0.113 (0.120)           | 0.226* (0.133)            | -0.042 (0.191) |
| Credit access                                   | 0.050 (0.043)           | 0.085* (0.047)            | 0.077 (0.068)  |
| Social network                                  | -0.004 (0.042)          | 0.054 (0.046)             | 0.062 (0.070)  |
| Agriculture information service access          | -0.019 (0.109)          | -0.169 (0.120)            | -0.097 (0.175) |
| Guangxi Province                                | -0.177 (0.109)          | -0.171 (0.119)            | 0.132 (0.177)  |
| Neighbors' smartphone use                       | 1.189*** (0.238)        |                           |                |
| Constant                                        | 5.168** (2.296)         | 2.539* (1.523)            | -7.002 (5.039) |
| $\rho_1$                                        |                         | -0.587* (0.306)           |                |
| $\rho_0$                                        |                         |                           | -1.113 (0.895) |
| Wald test of indep. eqns. ( $\rho_1 = \rho_0$ ) | Prob > $\chi^2 = 0.084$ |                           |                |
| Observations                                    | 901                     |                           |                |

Note: (i) Significance level: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . (ii) Guangdong Province is the reference region.

Abbreviations: CPC, Communist Party of China; DPDM, digital pest and disease management; ESP, endogenous switching probit model.

## 5.1 | Determinants of smartphone use

The first stage of the ESP model estimates the determinants of smartphone use. The results suggest that farmers' decisions on smartphone use are affected by age, education, health, cadre, and farm size (see the second column of Table 4). The negative and significant coefficient of age suggests that farmers' decisions about smartphone use are negatively associated with their age. In contrast, smartphone use is positively related to education and health. These results are in line with those of a considerable body of literature suggesting that younger, better-educated, and healthier farmers are more likely to adopt ICT such as mobile phones and the internet (Hübner & Hartje, 2016; Michels et al., 2020; Mwololo et al., 2019). Moreover, the likelihood of farmers' smartphone use increases if the number of cadres increases. The reason is that cadres may have more access to information on technological innovations. Farmers'

TABLE 5 ERM model results

| Variable                                                                   | Smartphone use          | Willingness to adopt DPDM |
|----------------------------------------------------------------------------|-------------------------|---------------------------|
| Smartphone use                                                             |                         | 0.352*** (0.121)          |
| Gender                                                                     | -0.183 (0.155)          | 0.019 (0.042)             |
| Age                                                                        | -0.181** (0.076)        | -0.033*** (0.011)         |
| Age square                                                                 | 0.001 (0.001)           | 0.000 (0.000)             |
| Education                                                                  | 0.088*** (0.020)        | 0.011* (0.006)            |
| Health                                                                     | 0.183* (0.099)          | 0.054* (0.030)            |
| Training participation                                                     | 0.033 (0.116)           | -0.030 (0.032)            |
| Farm year                                                                  | 0.004 (0.006)           | 0.000 (0.002)             |
| Labor                                                                      | -0.044 (0.036)          | -0.003 (0.009)            |
| CPC membership                                                             | 0.142 (0.088)           | 0.023 (0.026)             |
| Cadre                                                                      | 0.422*** (0.143)        | 0.058 (0.036)             |
| Wealth                                                                     | 0.072 (0.074)           | 0.042** (0.020)           |
| Farm size                                                                  | 0.015*** (0.003)        | 0.000 (0.000)             |
| Cooperative membership                                                     | 0.091 (0.119)           | 0.045 (0.033)             |
| Credit access                                                              | 0.049 (0.044)           | 0.027** (0.012)           |
| Social network                                                             | -0.001 (0.043)          | 0.012 (0.012)             |
| Agriculture information service access                                     | -0.015 (0.110)          | -0.040 (0.030)            |
| Guangxi Province                                                           | -0.163 (0.110)          | -0.025 (0.030)            |
| Neighbors' smartphone use                                                  | 1.214*** (0.245)        |                           |
| Constant                                                                   | 5.555** (2.218)         | 0.751** (0.335)           |
| Correlation of error terms of smartphone use and willingness to adopt DPDM | -0.275* (0.173)         |                           |
| Wald test                                                                  | Prob > $\chi^2$ = 0.000 |                           |
| Observations                                                               | 901                     |                           |

Note: (i) Significance level: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . (ii) Guangdong Province is the reference region.

Abbreviations: CPC, Communist Party of China; DPDM, digital pest and disease management; ERM, extended regression model.

decisions about smartphone use are also affected by farm size. This finding is supported by recent research on smartphone use among rural Chinese residents Ma, Grafton, et al., 2020. Note that the neighbors' smartphone use variable serves as an IV in the ESP model. The significant coefficient justifies the validity of the IV. This finding confirms the existence of peer effects on ICT use in rural China and is consistent with the findings of Ma et al. (2020).

## 5.2 | Determinants of willingness to adopt DPDM

The last two columns of Table 4 provide information on the determinants of smartphone users' and nonusers' willingness to adopt DPDM. The negative and significant coefficient of  $\rho_1$  shown in the lower part of the third

column indicates negative selection bias arising from unobserved heterogeneities. Moreover, the result of the Wald test rejects the null hypothesis of no correlation between error  $u_i$  and error  $\varepsilon_{0i}$  ( $\varepsilon_{1i}$ ). In other words, the treatment variable, that is, smartphone use, is not exogenous. This evidence indicates that the results would be biased if selection bias was not properly addressed.

The third column of Table 4 shows the results of equations for farmers' willingness to adopt DPDM among smartphone users. For smartphone users, the determinants of their willingness to adopt DPDM include age, wealth, cooperative membership, and credit access. In particular, the results suggest that younger smartphone users are more willing to adopt DPDM. Moreover, wealth is positively associated with willingness to adopt DPDM. Liquidity constraints have been identified as a barrier to hindering farmers' adoption of modern technology (Takahashi et al., 2019). Farmers that are rich and have better access to credit face fewer liquidity constraints. The result also indicates that cooperative members are more willing to adopt DPDM than nonmembers. This finding is plausible because one of the primary goals of agriculture cooperatives in developing countries is to promote advanced farming practices (Ma et al., 2017). Our finding is in line with that of Kiiza and Pederson (2012), who investigated the factors influencing Ugandan farmers' access to ICT-based market information and found a positive and significant role of membership in farmer associations and wealth.

The results of equations for farmers' willingness to adopt DPDM among smartphone nonusers are shown in the last column of Table 4. However, we did not find any control variable that is significantly associated with smartphone nonusers' willingness to adopt DPDM.

The results estimated from the ERM model are also presented to provide a further understanding of the impact of smartphone use on willingness to adopt DPDM. The results suggest that the determinants of smartphone users' and nonusers' willingness to adopt DPDM are different. To understand farmers' willingness to adopt DPDM from a more general perspective and for robustness check, we provide the results of ERM model in Table 5. The significant coefficient of the correlation between the errors from the main and auxiliary equation confirms the existence of endogeneity (see the bottom of Table 5). In addition to smartphone use, age, wealth, and credit access, which have the same relationship with DPDM as in the ESP model, the results of the ERM model suggest that litchi growers' willingness to adopt DPDM is also affected by education and health. The finding that education has a positive impact on willingness to adopt DPDM is in line with that of previous studies. Evidence suggests that highly educated cotton (Jenkins et al., 2011), corn (Gardezi & Bronson, 2019), and grain producers (Pivoto et al., 2019) are more likely to adopt digital agriculture innovations. Moreover, healthier farmers may be more capable of field data collection and human-smartphone interaction.

### 5.3 | Treatment effects and heterogeneity effects

According to Table 6, the estimated ATT is 0.190. The coefficient of the estimated ATT is significant at the 1% significance level. This result indicates that smartphone users have a 19 percentage point higher probability of willingness to adopt DPDM than their counterfactual users. Moreover, the estimated ATU is 0.175, which is statistically significant at the 1% level. This result suggests that the probability of willingness to adopt DPDM by nonusers would increase by 17.5 percentage points if they use smartphones. These results confirm the positive role of smartphone use on willingness to adopt DPDM. This finding is in line with the findings of Ogutu et al. (2014), whose study finds that Kenyan farmers who have mobile phones are more likely to adopt ICT-based market information.

Based on ATT and ATU, the transitional heterogeneity equals 0.015. This result suggests that the treatment effect for smartphone users is larger than that of nonusers. In other words, smartphone users are more inclined to adopt digital innovations. This finding highlights the need to promote smartphone coverage in rural areas. In addition, the base heterogeneity effects for the willingness to adopt group and the unwillingness to adopt group are 0.144 and 0.129, respectively.

TABLE 6 Treatment effects estimation results

|                       | Predictions      |                    | Treatment effect (ATT/ATU/TH) | T value |
|-----------------------|------------------|--------------------|-------------------------------|---------|
|                       | Willing to adopt | Unwilling to adopt |                               |         |
| Smartphone user       | 0.436 (0.182)    | 0.246 (0.160)      | 0.190 (0.196)***              | 18.197  |
| Smartphone nonuser    | 0.292 (0.242)    | 0.117 (0.097)      | 0.175 (0.204)***              | 12.876  |
| Heterogeneity effects | 0.144            | 0.129              | 0.015                         |         |

Note: (i) Significance level: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Abbreviations: ATT, average treatment effect on the treated; ATU, average treatment effect on the untreated; TH, treatment effect on the treated.

## 6 | CONCLUSION

Finding digital solutions for agricultural transformation is not a new strategy. It is widely believed that digital farming has the potential to address the challenges facing agriculture and rural development, including food insecurity, poor human nutrition, rural poverty, environmental pollution, and climate change (Klerkx et al., 2019; Tsan et al., 2019). However, the potential of digital farming cannot be fully realized without the engagement of smallholder farmers. This study evaluates the factors that drive farmers' willingness to adopt DPDM, focusing on smartphone use, using 928 cross-sectional litchi farm household datasets. Our empirical results indicate a positive influence of smartphone use on willingness to adopt DPDM. Moreover, we find that the determinants of smartphone users' and nonusers' willingness to adopt DPDM are different.

Our findings highlight the need to promote the use of smartphones in rural areas. We find that age, education, health, cadre, and farm size affect farmers' decisions on smartphone use. Moreover, age, education, health, wealth, cooperative membership, and credit access exert significant impacts on farmers' willingness to adopt DPDM. Therefore, governments should increase investment in rural public education and health services to promote smartphone adoption and use in agriculture. Moreover, it is necessary to provide smallholder farmers with financial support and credit access and encourage them to participate in agriculture cooperatives to facilitate the adoption of DPDM.

The limitation of this study is that we fail to control for the interviewer fixed effects. In this study, farmers had little knowledge of DPDM. To ensure farmers understand the question and give solid answers, enumerators followed the manual and briefly introduced the DPDM app to respondents. In this regard, respondents' willingness to adopt DPDM might be affected by the characteristics of the individual enumerator. It is suggested that future studies should record the respondent–enumerator pairs to control for the interviewer fixed effects.

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## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## APPENDIX A

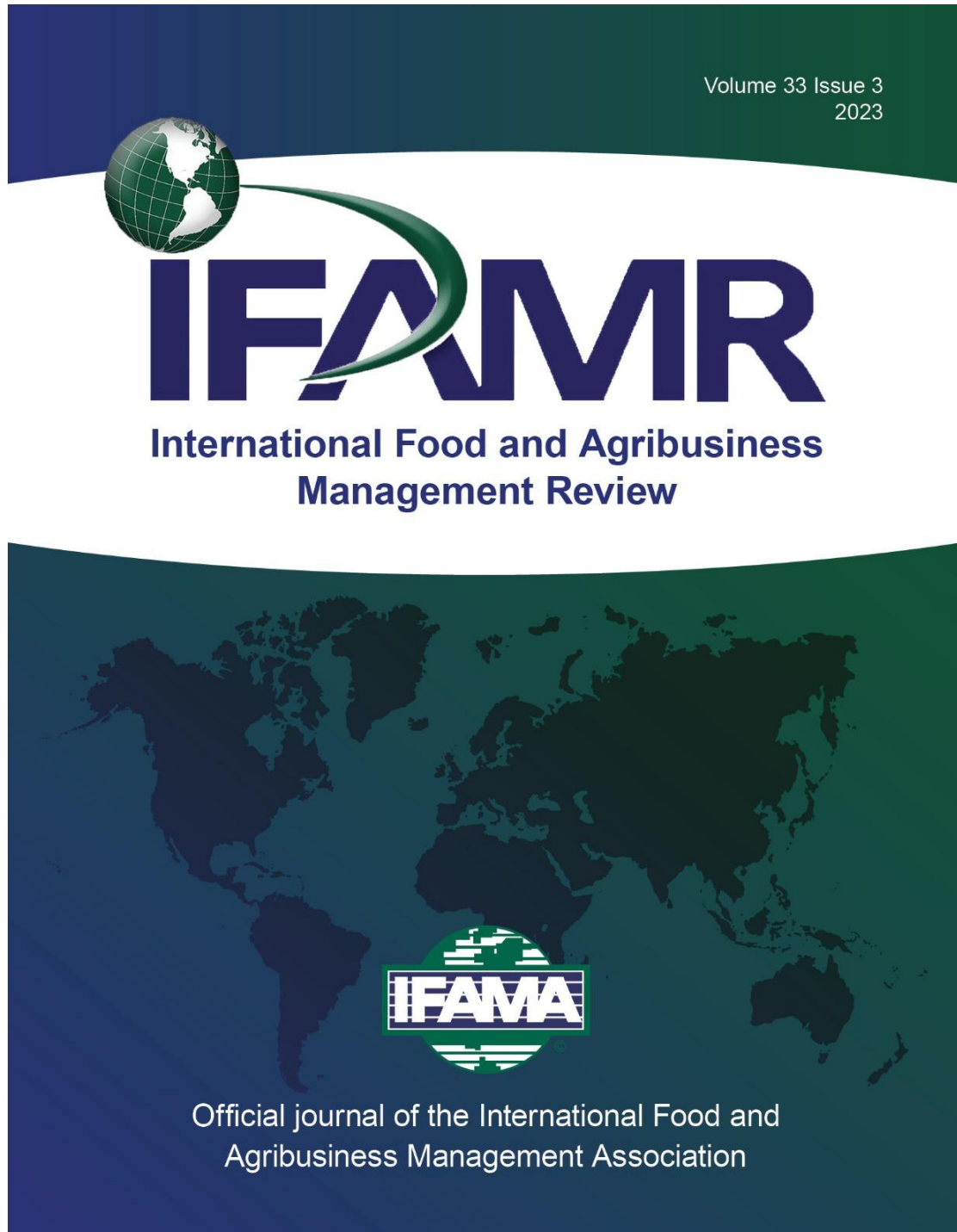
See Table A1.

**TABLE A1** Validity test for instrumental variable

| Variable                               | Willingness to adopt |
|----------------------------------------|----------------------|
| Smartphone use                         | 0.630*** (0.125)     |
| Gender                                 | 0.029 (0.141)        |
| Age                                    | −0.083** (0.041)     |
| Age square                             | 0.001(0.000)         |
| Education                              | 0.057*** (0.019)     |
| Health                                 | 0.291** (0.111)      |
| Training participation                 | −0.095 (0.113)       |
| Farm year                              | 0.002 (0.005)        |
| Labor                                  | −0.005 (0.033)       |
| Party membership                       | 0.095 (0.085)        |
| Cadre                                  | 0.188* (0.113)       |
| Wealth                                 | 0.169** (0.071)      |
| Farm size                              | 0.001 (0.001)        |
| Cooperative membership                 | 0.188* (0.110)       |
| Credit access                          | 0.101** (0.040)      |
| Social network                         | 0.047 (0.040)        |
| Agriculture information service access | −0.150 (0.104)       |
| Guangxi Province                       | −0.101 (0.103)       |
| Neighbors' smartphone use              | −0.078 (0.215)       |
| Constant                               | 0.413 (1.145)        |
| Observations                           | 901                  |

Note: (i) Significance level: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . (ii) Guangdong Province is the reference region.

2. 3. Impact of smartphone use on production outsourcing:  
evidence from litchi farming in southern China





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## Impact of smartphone use on production outsourcing: evidence from litchi farming in southern China

### RESEARCH ARTICLE

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### Abstract

There is a great deal of evidence suggesting that information and communication technology (ICT) and agricultural production outsourcing can improve farm productivity and farmers' welfare. However, less is known about the relationship between modern ICT use and agricultural production outsourcing. Drawing upon a survey of 855 litchi growers from southern China, this study estimates the effect of smartphone use on farmers' decisions regarding agricultural production outsourcing. A novel genetic matching method is employed to mitigate the selection bias associated with self-selected smartphone use. Our result confirms the positive role of smartphone use in increasing the number of production tasks outsourced by litchi growers. Moreover, smartphone users are more likely to outsource both labor-intensive and technology-intensive tasks than nonusers. In addition, the treatment effect of smartphone use varies with each specific litchi production task. Our findings highlight the importance of improving smartphone adoption among farmers to promote agricultural production outsourcing.

**Keywords:** smartphone, agricultural production outsourcing, genetic matching, litchi growers, rural China  
**JEL code:** Q18

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## 1. Introduction

China has made great achievements in economic development since the introduction of the reform and opening-up policy in 1978. In 2020, the gross domestic product of China was 14,722.73 billion US dollars according to the World Bank.<sup>1</sup> In the same year, the Seventh National Population Census of China revealed that the urbanization rate reached 63.89%.<sup>2</sup> Rapid urbanization and industrialization have triggered rural-urban labor migration and environmental degradation, which create pressure on the sustainability of small farms and Chinese food security (Liu *et al.*, 2010; Su *et al.*, 2011; Wang *et al.*, 2015).

There is a great deal of evidence suggesting that smartphone use and agricultural production outsourcing have the potential to overcome the disadvantages of the current Chinese farming system, such as small-scale farming, aging farmers, labor shortages, lack of machine ownership, and low modern technology adoption rate. Agricultural production outsourcing is expected to reduce smallholder farmers' input costs and increase output profits via the division of labor and economies of scale. By outsourcing agricultural production tasks to individuals or organizations with machine ownership and relevant skills, smallholder farmers can reduce production costs, enhance productivity, and enjoy more leisure time (Deng *et al.*, 2020; Mi *et al.*, 2020; Zhang *et al.*, 2018). The use of information and communication technology (ICT) can alleviate information asymmetry and reduce transaction costs in the agricultural sector (Aker, 2011; Aker *et al.*, 2016; Jensen, 2010). Recently, Chinese farmers have gradually adopted smart devices (especially smartphones) and benefited from the use of these modern ICT tools (Ma *et al.*, 2018; Nie *et al.*, 2020; Zheng and Ma, 2021b). Smartphone use enables rural households to connect to the internet without access to landline networks. In addition to basic functions such as making phone calls and sending text messages, smartphone users are able to take pictures, share videos, and customize their extension services using software applications (apps). Given these benefits of smartphone use, understanding the relationship between smartphone use and agricultural production outsourcing could provide evidence to effectively upscale the significant contributions of these two objects to improve rural sustainable development in developing countries.

The primary objective of this study is, therefore, to investigate the effect of smartphone use on agricultural production outsourcing. Our main finding is that smartphone use positively affects farmers' decisions regarding agricultural production outsourcing. Moreover, we divide the tasks into labor-intensive and technology-intensive groups and find positive effects of smartphone use on the number of labor- and technology-intensive tasks outsourced. In addition, the results suggest that the treatment effect of smartphone use varies with each specific production task. Our findings serve as a reference for the design of policies aiming to promote agricultural production outsourcing through the adoption of smartphones.

The contribution of this study is threefold. First, this study adds to the literature on the impact of ICT adoption on supporting sustainable agricultural production and rural development by estimating the effects of smartphone use on production outsourcing. There is extensive evidence that ICT use improves the welfare of smallholder farmers by raising income, diversifying income sources, smoothing consumption, and improving psychological health and food security (Beuermann, 2015; Leng *et al.*, 2020; Ma *et al.*, 2020a; Min *et al.*, 2020; Twumasi *et al.*, 2021; Zheng and Ma 2021a; Zhu *et al.*, 2020a,b, 2021b). Mobile phone- and internet-using farmers can receive timely information, improve knowledge of advanced technologies and are more likely to adopt modern farming practices (Cai *et al.*, 2022; Campenhout *et al.*, 2021; Kiiza and Pederson, 2012; Larochelle *et al.*, 2019; Ogutu *et al.*, 2014; Shiferaw *et al.*, 2015). In rural China, ICT users adopt more sustainable agricultural practices (Ma and Wang, 2020) and are more willing to use e-commerce (Ma *et al.*, 2020b) than nonusers. Internet use improves farm technical efficiency (Zheng *et al.*, 2021; Zhu *et al.*, 2021a) and reduces pesticide use (Zhao *et al.*, 2021) and cropland abandonment (Deng *et al.*, 2019). However, to the best of our knowledge, no previous study has focused on the effect of smartphone use on agricultural production outsourcing.

<sup>1</sup> World Bank data: <https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CN>

<sup>2</sup> Main data from the Seventh National Population Census of China: [http://www.stats.gov.cn/english/PressRelease/202105/t0210510\\_1817185.html](http://www.stats.gov.cn/english/PressRelease/202105/t0210510_1817185.html)

where  $T$  indicates the smartphone use status.  $Y$  is the farmer's decision on agricultural production outsourcing. It is independent of  $T$  conditional on a covariance matrix of  $X$ .

Genetic matching matches the covariates associated with the outcome variable. Existing research suggests that farmers' decisions on outsourcing service use are determined by household characteristics (e.g. age, education, farm size), crop type, region, and specific task (Deng *et al.*, 2020; Ji *et al.*, 2017; Mi *et al.*, 2020; Sun *et al.*, 2018; Zhang *et al.*, 2018). In this regard, we include a range of household head- and farm-level variables, such as smartphone use, gender, age, education, health, training participation, family labor, party membership, cadre, share of litchi income, farm size, income, outsourcing service access, and outsourcing service provider in matrix  $X$ . The descriptions of the variables selected are presented in the next section.

Genetic matching is able to find the best measure from a range of distance metrics to optimize the postmatching covariate balance within a certain generation size. In particular, it creates an additional weight matrix ( $W$ ) associated with each potential distance metric. The weight matrix ( $W$ ) is used to document the relative importance of each covariate. It should be noted that the propensity score is also included as one of the covariates to realize the balance between the treatment and control groups. Essentially, genetic matching matches the treatment-control pairs by minimizing the Generalized Mahalanobis Distance (GMD) defined as follows (Diamond and Sekhon, 2013; Sekhon, 2011):

$$GMD(X_T, X_C, W) = \sqrt{(X_T - X_C)^T (S^{-1/2})^T W (S^{-1/2}) (X_T - X_C)} \quad (2)$$

where  $W$  is the  $k \times k$  positive definite weight matrix and  $S$  is the sample covariance matrix of  $X$ .  $X_T$  represents the covariates of the treatment group.  $X_C$  indicates the covariates of the control group. All elements of  $W$  are restricted to 0 except those down the main diagonal, which consists of  $k$  parameters that must be chosen.

Then, genetic matching automates the iterative process to check and improve the covariate balance by constantly updating the weight  $W$  toward a better overall covariate balance. Even though genetic matching does not require estimating the propensity score, the method will achieve better balance if a propensity score is incorporated (Sekhon, 2011). As expected, the overall covariate balance will be improved and converge asymptotically as the size of generation (i.e. times of weight  $W$  update) increases (Diamond and Sekhon, 2013). In this regard, we do not need to check the balance of covariates after matching due to the iterative process and optimal algorithm. This alleviates concerns about the mis specified problem of the treatment model. As genetic matching can be used with any arbitrary matching method (Diamond and Sekhon, 2013), we applied one-to-one matching with replacement in this study.

### 3. Data, variable definition, and descriptive statistics

#### 3.1 Data

We used a household survey conducted from July 2020 to August 2020. A questionnaire that contains blocks of information, including household demographics, litchi production, and outsourcing behaviors, was applied for data collection. Before the survey, we modified the questionnaire based on a small-scale field test. The survey team members were graduate students selected from South China Agricultural University. They were trained on how to conduct interviews by the leading experts.

We applied a multistage sampling procedure to collect data. In the first stage, we selected the top two litchi-producing provinces in China (i.e. Guangdong Province and Guangxi Province). Four litchi-producing cities (Huizhou, Lianjiang, Maoming, and Yangjiang) in Guangdong Province and two cities (Qinzhou and Yulin) in Guangxi Province were selected in the second stage. In the third stage, we randomly selected one or two counties from each city. Within each selected county, two towns were randomly selected. In each town surveyed, we randomly selected approximately 25 farmers. As a result, we obtained 924 household

samples. Finally, we selected 855 samples for this study after dropping 39 households that did not engage in litchi production and 30 samples due to incomplete information.

### 3.2 Variable definition and descriptive analysis

#### ■ Litchi production task description and outsourcing rate

We found that litchi growers in surveyed areas outsource production tasks, including starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, pruning, fruit thinning, flower thinning, girdling, and grafting, to relatives and friends, large producers, agriculture cooperatives, and agriculture service companies. The definitions of these 11 litchi production tasks are shown in Table 1. Following the advice of CNLLITS experts, we define starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, and harvesting as labor-intensive tasks. Currently, these six tasks require intensive labor investment. In contrast, pruning, fruit thinning, flower thinning, girdling, and grafting rely more on machines, knowledge, and skills. Thus, these five tasks are categorized as technology-intensive tasks.

The last column of Table 1 presents the outsourcing rate of each litchi production task. Among the 855 surveyed farmers, harvesting was the most outsourced task, with an outsourcing rate of 28.9%. Grafting and pruning are the second- and third-most outsourced tasks. The outsourcing rates are 15.7 and 12.0%, respectively. The outsourcing rates of the other eight tasks are lower than 10%. These results suggest that agricultural production outsourcing services have not been widely adopted by litchi farmers in southern China.

**Table 1.** Litchi production task description and outsourcing rate.

|                                   | Description and measurement                                                        | Outsourcing rate <sup>1</sup> |
|-----------------------------------|------------------------------------------------------------------------------------|-------------------------------|
| <b>Labor-intensive tasks</b>      |                                                                                    |                               |
| Starter fertilizer application    | Apply starter fertilizer for a new production cycle. 1=outsourced, 0=otherwise     | 0.089 (0.285)                 |
| Regular fertilizer application    | Apply regular fertilizer during litchi production cycle. 1=outsourced, 0=otherwise | 0.081 (0.273)                 |
| Weeding                           | Remove unwanted plants in litchi orchard. 1=outsourced, 0=otherwise                | 0.075 (0.263)                 |
| Plant protection                  | Spray pesticide. 1=outsourced, 0=otherwise                                         | 0.085 (0.280)                 |
| Irrigation                        | Water litchi tree. 1=outsourced, 0=otherwise                                       | 0.042 (0.201)                 |
| Harvesting                        | Pick litchi. 1=outsourced, 0=otherwise                                             | 0.289 (0.454)                 |
| <b>Technology-intensive tasks</b> |                                                                                    |                               |
| Pruning                           | Remove some litchi trees' branches, buds, or roots. 1=outsourced, 0=otherwise      | 0.120 (0.323)                 |
| Fruit thinning                    | Remove some litchi flowers. 1=outsourced, 0=otherwise                              | 0.042 (0.201)                 |
| Flower thinning                   | Remove some litchi fruitlets. 1=outsourced, 0=otherwise                            | 0.068 (0.252)                 |
| Girdling                          | Remove litchi trees' bark. 1=outsourced, 0=otherwise                               | 0.008 (0.261)                 |
| Grafting                          | Connect scion and stock plants. 1=outsourced, 0=otherwise                          | 0.157 (0.364)                 |

<sup>1</sup> Mean and standard deviation (in parentheses).

### ■ Characteristics of litchi farmers

Table 2 presents the definition and summary of the treatment and covariate variables selected in this study. Our data show that 61% of surveyed farmers are smartphone users. This result is close to the Chinese rural internet penetration rate (55.9%) estimated by the China Internet Network Information Center in 2020.<sup>3</sup> Approximately 87% of household heads are male. The average age of the head of household is 57 years old. Approximately 64, 23 and 17% of household heads are training participants, party members, and village cadres, respectively. The average size of litchi orchards is approximately 1.3 ha. An average household generates 43% of its income from litchi farming. On average, the sample households have four members who are 16-65 years old. In addition, approximately 14% of farmers reported the existence of outsourcing service providers within the community.

### ■ Difference in outsourcing decisions between smartphone users and nonusers

Table 3 provides information regarding the difference between smartphone users and nonusers on outsourcing decisions. The results show that litchi growers who use smartphones are more likely to outsource all 11 production tasks than nonusers. Moreover, from the bottom of Table 3, we find that an average farmer in the treatment group outsourced 1.519 tasks. The figure for nonusers is 0.504. The difference between smartphone users and nonusers in the number of tasks outsourced is 1.015, which is significant at the 1% level based on the *t*-test. In addition, smartphone users outsourced more labor-intensive and technology-intensive tasks than their counterparts. On average, smartphone users outsourced 0.902 and 0.617 labor-intensive and technology-intensive tasks, respectively. The figures for nonusers are 0.287 and 0.218, respectively.

<sup>3</sup> Summary report of the China Internet Network Information Center: [http://www.gov.cn/sinwen/2021-02/03/content\\_5584518.htm](http://www.gov.cn/sinwen/2021-02/03/content_5584518.htm)

**Table 2.** Definition and summary of treatment and covariate variables.

| Variable                     | Definition                                                                                                    | Mean (SD) <sup>1</sup> |
|------------------------------|---------------------------------------------------------------------------------------------------------------|------------------------|
| Smartphone use               | 1=smartphone user, 0=otherwise                                                                                | 0.608 (0.488)          |
| Gender                       | 1=male, 0=female                                                                                              | 0.869 (0.338)          |
| Age                          | Year of household head's age                                                                                  | 57.318 (10.405)        |
| Education                    | 1=elementary school, 2=middle school, 3=high school, 4=college                                                | 2.020 (0.816)          |
| Health                       | 1=good, 0=normal, -1=bad                                                                                      | 0.743 (0.498)          |
| Training participation       | 1=agriculture training participant, 0=otherwise                                                               | 0.643 (0.370)          |
| Family labor                 | Number of 16-65 years old household members                                                                   | 4.116 (1.607)          |
| Party membership             | 1=member of Communist Party of China, 0=otherwise                                                             | 0.231 (0.422)          |
| Cadre                        | 1=village cadre, 0=otherwise                                                                                  | 0.166 (0.372)          |
| Share of litchi income       | The percentage of income generated from litchi farming                                                        | 42.598 (35.976)        |
| Farm size                    | Size of litchi orchard (ha)                                                                                   | 1.253 (1.157)          |
| Income                       | Natural log of income per capita (10,000 Yuan <sup>2</sup> )                                                  | 0.064 (43.039)         |
| Outsourcing service access   | Perception on the easy access to outsourcing service, ranging from 1-5, 1=strongly disagree, 5=strongly agree | 3.273 (1.145)          |
| Outsourcing service provider | 1=existence of agricultural production outsourcing service provider within the community, 0=otherwise         | 0.144 (0.351)          |
| Huizhou                      | 1=Huizhou farmer, 0=otherwise                                                                                 | 0.078 (0.269)          |
| Lianjiang                    | 1=Lianjiang farmer, 0=otherwise                                                                               | 0.117 (0.322)          |
| Maoming                      | 1=Maoming farmer, 0=otherwise                                                                                 | 0.230 (0.421)          |
| Yangjian                     | 1=Yangjian farmer, 0=otherwise                                                                                | 0.098 (0.298)          |
| Qinzhou                      | 1=Qinzhou farmer, 0=otherwise                                                                                 | 0.193 (0.395)          |

<sup>1</sup> SD = standard deviation.

<sup>2</sup> 1 USD = 6.36 Yuan.

**Table 3.** Differences in outsourcing decisions between smartphone users and nonusers.

|                                                 | Users <sup>1</sup> | Nonusers <sup>1</sup> | Mean difference <sup>2,3</sup> |
|-------------------------------------------------|--------------------|-----------------------|--------------------------------|
| Starter fertilizer application                  | 0.131 (0.337)      | 0.023 (0.153)         | 0.107***                       |
| Regular fertilizer application                  | 0.121 (0.327)      | 0.018 (0.133)         | 0.103***                       |
| Weeding                                         | 0.112 (0.315)      | 0.018 (0.133)         | 0.094***                       |
| Plant protection                                | 0.131 (0.337)      | 0.015 (0.121)         | 0.116***                       |
| Irrigation                                      | 0.065 (0.247)      | 0.006 (0.077)         | 0.059***                       |
| Harvesting                                      | 0.342 (0.475)      | 0.206 (0.405)         | 0.136***                       |
| Pruning                                         | 0.160 (0.366)      | 0.060 (0.237)         | 0.100***                       |
| Fruit thinning                                  | 0.063 (0.244)      | 0.009 (0.094)         | 0.055***                       |
| Flower thinning                                 | 0.100 (0.300)      | 0.018 (0.133)         | 0.082***                       |
| Girdling                                        | 0.108 (0.310)      | 0.021 (0.143)         | 0.087***                       |
| Grafting                                        | 0.187 (0.390)      | 0.110 (0.314)         | 0.076**                        |
| Number of tasks outsourced                      | 1.519 (2.844)      | 0.504 (1.267)         | 1.015***                       |
| Number of labor-intensive tasks outsourced      | 0.902 (1.678)      | 0.287 (0.763)         | 0.615***                       |
| Number of technology-intensive tasks outsourced | 0.617 (1.268)      | 0.218 (0.641)         | 0.399***                       |
| Observations                                    | 520                | 335                   |                                |

<sup>1</sup> Mean and standard deviation (in parentheses).

<sup>2</sup> A *t*-test was applied to estimate the significance of the mean difference.

<sup>3</sup> \*\* and \*\*\* denote significance at the 5 and 1% levels, respectively.

## 4. Results and discussion

### 4.1 Covariate balance checking

Genetic matching uses a search algorithm to iteratively check and improve covariate balance. Following Sekhon and Grieve (2012) and Austin (2008), we provide information on the standardized mean difference, D-statistic, and *P*-value for the postmatching covariate balance check (Table 4). It should be noted that *P*-values are taken from *t*-tests for binary variables (i.e. gender, training participation, party membership) and from the bootstrapped Kolmogorov-Smirnov (KS) test for continuous variables (i.e. age, share of litchi income, farm size). The decrease in difference in means (standardized mean difference) and the mean discrepancies (D-statistic) may result in a higher *P*-value, which suggests an improvement in balance across the covariate distribution.

We find from Table 4 that the treatment and control groups are imbalanced before matching. Smartphone users and nonusers had different characteristics in 12 out of 18 covariates ( $P < 0.1$ ). Typically, smartphone users are 10 years younger than nonusers. This difference is significant at the 1% level. Moreover, smartphone users are more likely to have better health and education, access to training and outsourcing services, larger farm sizes, and party memberships. After genetic matching, the age difference decreased to 3 years and was no longer statistically significant. Significant differences persisted in only 3 out of 18 covariates. These results suggest that the covariate balance is well improved in the treatment and control groups (Frey, 2014).

To improve our understanding and for comparison purposes, we also employ PSM (one-to-one matching with replacement) to mitigate selection bias and estimate the impact of smartphone use on agricultural production outsourcing. To avoid the compression of propensity scores near zero and one, we follow Sekhon (2011) and use logistic regression to estimate the propensity score model. From Supplementary Table S1, we find that variables including age, education, party membership, cadre, share of litchi income, and farm size significantly influence farmers' decision on smartphone use. The marginal effects of these variables are -0.032, 0.037, 0.129, 0.153, 0.001, and 0.004, respectively. The finding that age has a negative impact on smartphone use is in line with that of previous studies (e.g. Kiiza and Pederson, 2012; Ma *et al.*, 2018;

**Table 4.** Covariate balance results.<sup>1</sup>

|                              | Before matching |              |                  |                |                      | After matching |        |       |         |
|------------------------------|-----------------|--------------|------------------|----------------|----------------------|----------------|--------|-------|---------|
|                              | Treatment mean  | Control mean | SMD <sup>2</sup> | D <sup>3</sup> | P-value <sup>4</sup> | Control mean   | SDM    | D     | P-value |
| Gender                       | 0.854           | 0.893        | -0.110           | 0.039          | 0.093                | 0.867          | -0.038 | 0.013 | 0.380   |
| Age                          | 53.098          | 63.868       | -1.044           | 0.457          | 0.000                | 56.456         | -0.353 | 0.160 | 0.160   |
| Education                    | 2.212           | 1.722        | 0.607            | 0.259          | 0.000                | 2.002          | 0.260  | 0.088 | 0.188   |
| Health                       | 0.815           | 0.629        | 0.422            | 0.168          | 0.000                | 0.815          | 0.000  | 0.004 | 0.971   |
| Training participation       | 0.685           | 0.579        | 0.227            | 0.105          | 0.002                | 0.683          | 0.004  | 0.002 | 0.903   |
| Family labor                 | 4.110           | 4.125        | -0.010           | 0.032          | 0.667                | 4.182          | -0.048 | 0.071 | 0.254   |
| Party membership             | 0.279           | 0.158        | 0.269            | 0.121          | 0.000                | 0.265          | 0.030  | 0.013 | 0.203   |
| Cadre                        | 0.223           | 0.078        | 0.349            | 0.145          | 0.000                | 0.219          | 0.009  | 0.004 | 0.557   |
| Share of litchi income       | 44.172          | 40.155       | 0.111            | 0.068          | 0.266                | 44.556         | -0.011 | 0.079 | 0.278   |
| Farm size                    | 24.383          | 9.872        | 0.272            | 0.173          | 0.000                | 14.867         | 0.178  | 0.088 | 0.088   |
| Income                       | 0.324           | -0.340       | 0.518            | 0.206          | 0.000                | 0.072          | 0.196  | 0.096 | 0.209   |
| Outsourcing service access   | 3.294           | 3.239        | 0.048            | 0.037          | 0.036                | 3.203          | 0.078  | 0.081 | 0.000   |
| Outsourcing service provider | 0.165           | 0.110        | 0.148            | 0.055          | 0.020                | 0.133          | 0.088  | 0.033 | 0.308   |
| Huizhou                      | 0.092           | 0.057        | 0.123            | 0.036          | 0.047                | 0.031          | 0.212  | 0.062 | 0.000   |
| Lianjiang                    | 0.121           | 0.110        | 0.033            | 0.011          | 0.632                | 0.123          | -0.006 | 0.002 | 0.873   |
| Maoming                      | 0.237           | 0.221        | 0.037            | 0.016          | 0.595                | 0.200          | 0.086  | 0.037 | 0.212   |
| Yangjian                     | 0.087           | 0.116        | -0.106           | 0.030          | 0.164                | 0.102          | -0.055 | 0.015 | 0.323   |
| Qinzhou                      | 0.213           | 0.161        | 0.127            | 0.052          | 0.053                | 0.196          | 0.042  | 0.017 | 0.121   |

<sup>1</sup> Yulin is the reference city.<sup>2</sup> SMD = standardized mean difference.<sup>3</sup> The D-statistic is the maximum difference in the empirical quantile-quantile plot.<sup>4</sup> P-values are from paired *t*-tests for binary variables and from the bootstrapped KS-test for continuous variables.

Ma and Wang, 2020; Zheng and Ma, 2021b; Zhu *et al.*, 2021a). Moreover, existing studies, such as Ma *et al.* (2018) and Deng *et al.* (2019), find that education and farm size are positively associated with farmers' decisions on smartphone and internet use. Supplementary Table S2 provides information with regard to the covariate balance results using PSM. We find that a significant difference remains in 7 out of 18 covariates. This suggests that genetic matching achieved better overall covariate balance than PSM.

#### 4.2 Average treatment effect for the treated estimation

The ATT estimation results are presented in Table 5. From the top of the table, we find that smartphone use positively influences the number of tasks outsourced by litchi growers. The estimated ATT is 0.465 and statistically significant at the 5% level. This suggests that the average household in the treated group (i.e. smartphone users) will outsource 0.465 more tasks than it would if it did not use smartphones. Our finding is in line with Deng *et al.* (2019). Their research reveals that internet use is positively associated with farmers' decisions on outsourcing. Smartphone use facilitates agricultural production outsourcing through the potential channel of lowering transaction costs. Search and negotiation costs occur when smallholder farmers try to hire individuals and organizations for production tasks. Rural-urban migration results in rural labor shortages and rising labor costs. It is difficult to find and costly to use outsourcing services from traditional outsourcing service providers (e.g. fellow small farmers, relatives, and friends). Moreover, there is only a small number of modern outsourcing service providers (e.g. large producers, agriculture cooperatives, and agriculture service companies) who own machines and specialize in agricultural production. Combined with dispersed rural settlements and inconvenient transportation, the search costs for outsourcing services are high for litchi farmers in southern China. It is also difficult for smallholder farmers to negotiate the contract with outsourcing service providers, monitor the task outsourced, and evaluate the performance from a long-

term perspective. As 98% of Chinese rural villages are covered by 4G mobile signals,<sup>4</sup> smartphone users can connect to the internet and communicate with outsourcing service providers in a timely and low-cost manner. Moreover, farmers can use smartphones to collect and store information (e.g. contracts, pictures, and videos) for monitoring and evaluation.

The estimated ATTs for the number of labor-intensive and technology-intensive tasks outsourced are 0.371 and 0.094, respectively. The coefficient of the former estimated ATT is statistically significant at the 5% level, and the latter is statistically significant at the 10% level. These results indicate a positive role of smartphone use on outsourcing both labor-intensive and technology-intensive tasks of litchi growers.

Additionally, we find that the treatment effect of smartphone use varies with each specific litchi production task. The estimated ATTs of smartphone use on starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, flower thinning, and girdling are 0.065, 0.085, 0.048, 0.069, 0.040, 0.063, 0.013, and 0.050, respectively. These coefficients are statistically significant at the 10% or higher level. Moreover, we find positive coefficients of the estimated ATTs of smartphone use on fruit thinning and pruning and negative ATTs of smartphone use on grafting. However, these coefficients are not significant. Our finding is in line with that of the existing research. In particular, Ji *et al.* (2017), Zhang *et al.* (2018), and Mi *et al.* (2020) confirm that the determinants of outsourcing decisions vary with the specific production tasks in rice, apple, and cotton farming, respectively. A possible explanation is that farm households have significant demand for certain labor-intensive outsourcing services. There are plenty of off-farm work opportunities in southern China. The use of outsourcing services can help litchi growers cope with labor shortages during the peak season and improve efficiency. For example, litchi is still harvested manually. Hiring skilled workers may help accelerate the fruit picking process without recalling household members who participate in off-farm work. Moreover, agricultural production outsourcing can assist farmers who lack production skills and machine ownership (Ji *et al.*, 2017; Zhang *et al.*, 2017). This may help explain our findings of the positive and significant effects of smartphone use on farmers' decisions regarding starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, flower thinning, and girdling outsourcing.

<sup>4</sup> China daily report: <http://www.chinadaily.com.cn/a/201908/02/WS5d43f3c6a310cf3e355639b3.html>

**Table 5.** Results of average treatment effect for the treated (ATT) estimation.

|                                                 | ATT (SE) <sup>1,2</sup> |
|-------------------------------------------------|-------------------------|
| Number of tasks outsourced                      | 0.465** (0.285)         |
| Number of labor-intensive tasks outsourced      | 0.371** (0.163)         |
| Number of technology-intensive tasks outsourced | 0.094* (0.139)          |
| Starter fertilizer application                  | 0.065* (0.035)          |
| Regular fertilizer application                  | 0.085*** (0.031)        |
| Weeding                                         | 0.048* (0.035)          |
| Plant protection                                | 0.069* (0.036)          |
| Irrigation                                      | 0.040** (0.026)         |
| Harvesting                                      | 0.063** (0.045)         |
| Pruning                                         | 0.021 (0.040)           |
| Fruit thinning                                  | 0.019 (0.028)           |
| Flower thinning                                 | 0.013* (0.034)          |
| Girdling                                        | 0.050* (0.033)          |
| Grafting                                        | -0.010 (0.047)          |

<sup>1</sup> SE = robust Abadie-Imbens standard errors.

<sup>2</sup> \*, \*\* and \*\*\* denote significance at the 10, 5 and 1% levels, respectively.

For comparison, we estimated the impact of smartphone use on farmers' decisions on agricultural production outsourcing using PSM, and the results are presented in Supplementary Table S3. The estimated ATT of smartphone use on the number of tasks outsourced using PSM is 0.755. Moreover, the results indicate that smartphone users will outsource 0.202 and 0.553 more labor-intensive and technology-intensive tasks, respectively. These findings confirm the positive effects of smartphone use on agricultural production outsourcing by litchi growers in southern China.

## 5. Conclusions

The promotion of modern ICT and agricultural production outsourcing is critical for the modernization of the Chinese small farming system. Using a sample of 855 litchi growers, this study investigates the relationship between smartphone use and farmers' decisions on agricultural production outsourcing. We employ a novel approach to control for self-selection bias for smartphone use. The genetic matching results show that smartphone use has a positive impact on agricultural production outsourcing. These results largely echo the results estimated from PSM. Moreover, we find that smartphone users tend to outsource more labor-intensive and technology-intensive tasks than nonusers. Among the 11 litchi production tasks, smartphone users were more likely to outsource tasks, including starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, flower thinning, and girdling, than nonusers. However, smartphone use does not significantly affect farmers' decisions on outsourcing pruning, fruit thinning, and grafting.

Our results yield several important policy implications. Agricultural production outsourcing may promote the use of machine and modern technologies in agricultural production. Since smallholders' outsourcing behavior is positively associated with smartphone use, the central and local governments should thus further improve the coverage and quality of rural mobile networks and promote the use of smartphones among farmers. Education is positively associated with farmers' decisions on smartphone use. Governments should also keep investing in rural education. Moreover, local governments should facilitate the supply of agricultural production outsourcing services in regions where there is active rural-urban migration. In particular, governments should encourage large producers, agriculture cooperatives, and agriculture service companies to provide professional outsourcing services to smallholder farmers. Governments should also cooperate with stakeholders (e.g. modern agricultural outsourcing service providers, agricultural extension workers, telecommunication companies, smartphone app developers) to disseminate agricultural outsourcing service information via smartphones. In this study, we measured agricultural production outsourcing as a binary variable, without taking into account the degree of outsourcing. It would be an interesting direction for future studies to look at the effects of smartphone use on the outsourcing degree among different agricultural production tasks.

## Supplementary material

Supplementary material can be found online at <https://doi.org/10.22434/IFAMR2021.0155>

**Table S1.** Logistic regression on smartphone use.

**Table S2.** Covariate balance results using PSM.

**Table S3.** Results of ATT estimation using PSM.

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## Conflict of interest

The authors declare that they have no conflict of interest.

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## 2. 4. Mobile Internet adoption and technology adoption extensity: evidence from litchi growers in southern China



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# Mobile Internet adoption and technology adoption extensivity: evidence from litchi growers in southern China

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## Abstract

**Purpose** – The purpose of this study is to examine the effects of mobile Internet adoption on technology adoption extensivity.

**Design/methodology/approach** – This study uses cross-sectional data collected in 2018 from 932 smallholder litchi farmers in Guangdong Province and Guangxi Province in southern China. A Poisson regression with endogenous treatment effects (ETPR) model is applied to estimate the effects of mobile Internet adoption on technology adoption extensivity.

**Findings** – The ETPR model results indicate that mobile Internet adoption can significantly enhance technology adoption extensivity. In addition, the extensivity of technology adoption is also determined by education level, training, share of litchi farming income, guidebook use and cooperative membership. Disaggregated analyses further confirm the positive impact of mobile Internet adoption on the number of capital- and labor-intensive technologies adopted.

**Originality/value** – This study contributes to the literature on agricultural technology adoption. The findings highlight the need to facilitate modern agricultural technology penetration by promoting the use of mobile Internet technologies.

**Keywords** Mobile Internet adoption, Technology adoption extensivity, Litchi farmer, Rural China, Poisson regression with endogenous treatment effects

**Paper type** Research paper

## 1. Introduction

Agriculture as a whole is facing great challenges arising from labor shortages and rising supply costs. These problems can be addressed by applying modern technology to agriculture (Schultz, 1964; Sunding and Zilberman, 2001; Bruinsma, 2003). However, the penetration rate of modern technology is relatively low in smallholder agricultural systems in developing countries (Muzari *et al.*, 2012; Mwangi and Kariuki, 2015). This low penetration rate limits the contribution of modern agricultural innovations to poverty alleviation, rural development and food security (Janvry and Sadoulet, 2002; Magrini and Vigani, 2016; Mendola, 2007; Pan *et al.*, 2018).

High transaction costs have been recognized as a limiting factor that restricts the adoption of technology by smallholder farmers (Zhang *et al.*, 2019; Dridi and Khraief, 2011; Odozi and

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*Ethics approval and consent to participate:* Not applicable

*Consent for publication:* Not applicable

*Availability of data and materials:* The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

*Conflict of interest:* The authors declare that they have no conflict of interest.

*Competing interests:* The authors declare that they have no competing interests.



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Omonona, 2013). Transaction costs may be incurred when farmers try to search for technology-related information, communicate with external technical suppliers or agricultural extension workers, purchase specialized machines and implement modern technologies. These costs are particularly high for smallholder farmers in developing countries (Gbadegesin and Popoola, 2020). On the one hand, smallholder farmers have less knowledge or are not aware of modern technology due to information asymmetry. On the other hand, a long distance to the market also leads to higher transaction costs of information searches, the transportation of goods and service delivery. High transaction costs can thus discourage smallholder farmers from engaging in market participation and technology adoption.

Over the last several decades, information and communication technology (ICT) has been introduced and widely adopted by populations around the globe. According to the World Bank, the share of the global Internet-using population has exceeded 40% (WorldBank, 2016). Moreover, the penetration rate of mobile phones in the lowest income 20% of the population in developing countries is approximately 70% (WorldBank, 2016). The benefits of ICT usage in the rural and agricultural sectors include improvements in agricultural market efficiency, reduced information asymmetry and increased market power among farmers (Jensen, 2010). There is abundant evidence that suggests that market information obtained through the use of ICT assist farmers' decision making (Tadesse and Bahiigwa, 2015; Jensen, 2007). ICT adoption also facilitates agricultural extension service delivery in rural areas (Fu and Akter, 2016; Baumüller, 2012).

A growing body of research finds evidence of a positive relationship between ICT adoption and agricultural technology adoption (Melguizo *et al.*, 2016; Yang and Zhang, 2020; Ma and Wang, 2020). One stream of work investigates the impact of ICT adoption on the intensity of agricultural technology adoption (Melguizo *et al.*, 2016; Yang and Zhang, 2020). In particular, Kiiza and Pederson (2012) find that Ugandan farmers who obtain information through the use of ICT increase their share of improved seeds for agricultural production. Ogotu *et al.* (2014) reveals that ICT-based MIS project participants in Kenya use more commercial seeds and fertilizers than their counterparts. As more agricultural innovations are introduced into rural areas, another interesting question may be related to the extensity of technology adoption, *i.e.*, the number of technologies adopted by a farmer. For example, in focusing on the adoption of sustainable technology, Ma and Wang (2020) suggest that rural Internet users apply more environmentally friendly technologies than nonusers.

This study contributes to the literature on agricultural technology adoption. Although it has been proven that obtaining agricultural extension services through the use of mobile phones has a positive impact on access to credit and farmers' awareness of and willingness to try new technologies (Fu and Akter, 2016; Baumüller, 2012), less is known about the impact of ICT adoption on the number of technologies adopted. Agricultural production is a complex process. Agro-food producers also face risks from the environment. To achieve better yields, farmers have to apply a combination of technologies for land preparation, irrigation, pest and disease control and harvest. ICT use facilitates information flows (Aker, 2011; Aker *et al.*, 2016; Jensen, 2010). By using ICTs (e.g. the Internet, mobile phone and radio), farmers can receive timely reminders from village cadres, fellow farmers, neighbors and agricultural extension workers. They can thus take care of their crops by using the proper technologies during the critical stages of production and for extreme weather events and pests and diseases outbreaks. Therefore, ICT adoption is expected to have a positive effect on the extensity of technology adoption. Moreover, different technologies may require different amounts of capital and labor input to carry out production activities. In this regard, we are also interested in exploring the effects of ICT adoption on the extensity of capital- and labor-intensive technology adoption.

A dataset that covers 932 litchi farmers in Guangdong Province and Guangxi Province in southern China is applied for the empirical analysis. China is the leading litchi producing

country in the world. Over the last several decades, litchi production in rural China has been increasingly driven by technology. Modern technologies for land preparation, irrigation, orchard management and pesticide control are becoming available to litchi growers. Local agricultural bureau, agricultural cooperative, Chinese National Litchi and Longan Industry Technology System (NLLITS), and elite litchi growers are the main sources for smallholders to obtain litchi technology information. The NLLITS was established in 2009. It is responsible for the promotion of the sustainable development of the Chinese litchi and longan industries. Chinese agricultural extension workers are encouraged to take advantage of mobile Internet technologies (Zhang *et al.*, 2016). For example, in addition to offline demonstration orchards in litchi concentrated regions, the NLLITS has developed online (e.g. a web portal and WeChat public account) channel to deliver agricultural extension services to farmers.

As suggested in previous works, farmers' ICT adoption is constrained by socioeconomic factors, such as age, gender, location, income and education level (Yang and Zhang, 2020; Fu and Akter, 2016; Melguizo *et al.*, 2016; Goldfarb and Prince, 2008; Martínez-Domínguez and Mora-Rivera, 2020). Failing to address endogeneity problem arising from both observed and unobserved factors would lead to biased results. We thus apply a Poisson regression with endogenous treatment effects (ETPR) to perform a rigorous estimation. Based on the basic count model, *i.e.* the Poisson regression model, the ETPR approach takes advantage of instrumental variables to solve endogeneity problems.

Our results show that on average, the sampled farmers have adopted 3.749 of the 11 technologies identified. Farmers who adopt mobile Internet adopt 12.2% more technologies on average than those who do not adopt mobile Internet. The results of disaggregated analyses suggest that mobile Internet users apply 14.1 and 10.4% more capital- and labor-intensive technologies than nonusers, respectively. Hence, farmers' adoption of mobile Internet can positively affect the number of technologies they adopt.

Since litchi trees can only be planted in tropical areas, this study is limited to Guangxi and Guangdong litchi growers. Our findings provide empirical evidence supporting the efforts of policymakers and interest groups in promoting mobile Internet technologies in litchi production areas. Our findings also have valuable implications for other litchi production regions in southern China (e.g. Fujian and Hainan) and for other litchi growing countries (e.g. India, Vietnam and Thailand). Moreover, applying modern technologies has great potential to improve the quality and quantity of agricultural outputs and thus raise farmers' incomes. This study to some extent also serves as a reference for the design of policies aiming to promote agricultural technologies through the use of ICT.

The next section is data collection and descriptive analysis. Estimation strategy is described in section 3. The results and discussions are presented in section 4. Finally, section 5 concludes.

## 2. Data collection and descriptive analysis

### 2.1 Data collection

NLLITS program established pilot stations in Maoming City, Zhanjiang City and Shenzhen City in Guangdong Province and Yulin City, Qinzhou City and Beihai City in Guangxi Province. These are the most concentrated litchi producing areas in China. In August 2018, the NLLITS survey team used a multistage sampling method for data collection. For location selection, the sampling method takes the distribution of litchi planting areas into account. For farmer selection, we followed the random sampling procedure. Specifically, we first divided 16 NLLITS demonstration counties in Maoming City, Zhanjiang City and Shenzhen City in Guangdong Province into five groups based on litchi planting area and randomly selected 1 county from each group. 5 counties were selected from Yulin City, Qinzhou City and Beihai City in Guangxi Province following the same rule. Second, towns were divided into large,

medium and small litchi producing towns based on litchi planting area. We randomly selected 1 town from the large and medium litchi producing groups, respectively. Third, we divided villages into large, medium and small litchi producing villages and randomly selected 1 village from the large and medium litchi producing groups, respectively. Finally, approximately 25 sample farmers were randomly selected from each village. As a result, the research team collected 943 household data from 40 villages, 20 towns, 10 counties and 6 cities in Guangdong Province and Guangxi Province (see Table A1 for detailed information).

The team used a structured questionnaire for data collection. The team members were trained by NLLITS experts before conducting the survey. Information regarding household member characteristics, ICT uses, farm size, cooperative membership, inputs and outputs, and technology used in litchi and longan production were collected. Finally, we used 932 samples for the empirical analysis after removing data with missing information and farmers who do not grow litchi.

## 2.2 Variable definition

On the advice of the NLLITS experts and from our frequent field visits (the NLLITS survey team has conducted a large-scale field survey every year since 2014), we compiled 11 litchi production technologies into a list. These technologies were widely available to farmers in the 2017–2018 production cycle. Table 1 presents descriptions and adoptions rate of the technologies selected. Among the 11 technologies, tree thinning, girdling, pruning, grafting, irrigating and fertigation are categorized as capital-intensive technologies because they require more capital investment than labor-intensive technologies (e.g. pesticide, insect-proof net, flower thinning, fruit thinning and bagging). The outcome variable, *i.e.*, technology adoption extensity, is then represented by the number of technologies adopted by a litchi grower. In this regard, technology adoption extensity is a count variable. Similarly, capital-intensive technology adoption extensity and labor-intensive technology adoption extensity refer to the cumulative amount of capital- and labor-intensive technologies adopted by a farmer, respectively.

As our treatment variable, the mobile Internet adoption variable takes a value of one if farmers use WeChat and zero otherwise. WeChat is one of the most popular smartphone apps in China. It was first introduced to the public as an online chat app in 2011. In addition to sharing information, users can browse the Internet, make online transactions, play online

| Technology                          | Description                                                                                              | Adoption rate |
|-------------------------------------|----------------------------------------------------------------------------------------------------------|---------------|
| <i>Capital-intensive technology</i> |                                                                                                          |               |
| Tree thinning                       | Remove part or part of the litchi tree                                                                   | 0.490 (0.500) |
| Girdling                            | Remove a strip of bark from around the entire circumference of either a branch or trunk of a litchi tree | 0.590 (0.492) |
| Pruning                             | Remove certain parts of a plant, such as branches, buds, or roots                                        | 0.619 (0.486) |
| Grafting                            | Connect scion and stock plants                                                                           | 0.395 (0.489) |
| Irrigating                          | Adopt spray or drip irrigation                                                                           | 0.043 (0.203) |
| Fertigation                         | Adopt an irrigation system which combines the injection of fertilizer                                    | 0.057 (0.232) |
| <i>Labor-intensive technology</i>   |                                                                                                          |               |
| Pesticide                           | Adopt pesticide                                                                                          | 0.882 (0.323) |
| Insect-proof net                    | Adopt insect-proof net                                                                                   | 0.008 (0.086) |
| Flower thinning                     | Remove some flowers                                                                                      | 0.427 (0.495) |
| Fruit thinning                      | Remove some fruitlets                                                                                    | 0.229 (0.420) |
| Bagging                             | Bag fruit on trees                                                                                       | 0.010 (0.098) |

**Table 1.**  
Technology  
description and  
adoption rate

games and order food using WeChat. The number of WeChat users exceeded 10 billion, and more than 45 billion messages were sent through WeChat each day in 2018. We found from the survey that agricultural extension workers, agricultural cooperative members and village cadres used WeChat to deliver agricultural extension services. In particular, they invited farmers to join WeChat groups and follow local agricultural bureau's and NLLITS's public accounts. Litchi growers can not only obtain information about advanced technologies through WeChat, but also interact with technicians and fellow farmers by sharing pictures and videos.

Following the previous research on ICT and agricultural technology adoption (Goldfarb and Prince, 2008; Martínez-Domínguez and Mora-Rivera, 2020; Chang and Just, 2009; Zhang *et al.*, 2019), we selected a set of control variables from household and farm perspectives. Table 2 provides definitions and descriptive statistics for the variables used in this study. In particular, we included gender, age, education level, health status, farming experience, farm size, labor, wealth, share of litchi farming income, guidebook use, cadre or party membership, off-farm work, training and cooperative membership as control variables. A set of regional dummies was also included to control for the city-level location fixed effect. In addition, a

| Variables                      | Definition                                                          | Mean (SD)       |
|--------------------------------|---------------------------------------------------------------------|-----------------|
| <i>Treatment variables</i>     |                                                                     |                 |
| Mobile Internet adoption       | 1 if farmer uses WeChat, 0 otherwise                                | 0.398 (0.490)   |
| <i>Outcome variables</i>       |                                                                     |                 |
| All technology                 | Number of technologies adopted (from 0 to 11)                       | 3.749 (1.861)   |
| Capital-intensive technology   | Number of capital-intensive technologies adopted (from 0 to 6)      | 2.194 (1.349)   |
| Labor-intensive technology     | Number of labor-intensive technologies adopted (from 0 to 5)        | 1.555 (0.888)   |
| <i>Control variables</i>       |                                                                     |                 |
| Gender                         | 1 if household head is male, 0 otherwise                            | 0.893 (0.310)   |
| Age                            | Year of household head's age                                        | 56.99 (10.960)  |
| Education level                | Year of household head's education                                  | 8.336 (2.944)   |
| Health status                  | Household head's health condition, 1 = good, 0 = normal; -1 = bad   | 0.736 (0.509)   |
| Farming experience             | Farming years of household head                                     | 22.910 (10.340) |
| Farm size                      | Litchi farming size (mu)                                            | 15.180 (34.390) |
| Labor                          | Number of family members who are 16–65 years old                    | 3.923 (1.830)   |
| Share of litchi farming income | Litchi income in the proportion of total household income (%)       | 40.280 (35.09)  |
| Guidebook use                  | 1 if farmer has guidebook, 0 otherwise                              | 0.209 (0.407)   |
| Cadre or party membership      | 1 if farmer has cadre or party membership, 0 otherwise              | 0.222 (0.416)   |
| Off-farm work                  | 1 if farmer has a off-farm work, 0 otherwise                        | 0.181 (0.385)   |
| Training                       | 1 if farmer participates in training, 0 otherwise                   | 0.565 (0.496)   |
| Cooperative membership         | 1 if farmer is cooperative member, 0 otherwise                      | 0.282 (0.450)   |
| Yulin                          | 1 if farmer locates in Yulin, 0 otherwise                           | 0.198 (0.399)   |
| Qinzhou                        | 1 if farmer locates in Qinzhou, 0 otherwise                         | 0.202 (0.401)   |
| Beihai                         | 1 if farmer locates in Beihai, 0 otherwise                          | 0.105 (0.307)   |
| Maoming                        | 1 if farmer locates in Maoming, 0 otherwise                         | 0.212 (0.409)   |
| Shenzhen                       | 1 if farmer locates in Shenzhen, 0 otherwise                        | 0.069 (0.253)   |
| Zhanjiang                      | 1 if farmer locates in Zhanjiang, 0 otherwise                       | 0.214 (0.410)   |
| <i>Instrumental variable</i>   |                                                                     |                 |
| Message                        | 1 if farmer ables to use mobile text messaging service, 0 otherwise | 0.501 (0.500)   |

Table 2.  
Variable definition and  
descriptive statistic

message variable that refers to a farmer's ability to use the mobile text messaging service was selected as an instrumental variable for model identification.

The effects of  
mobile Internet  
adoption

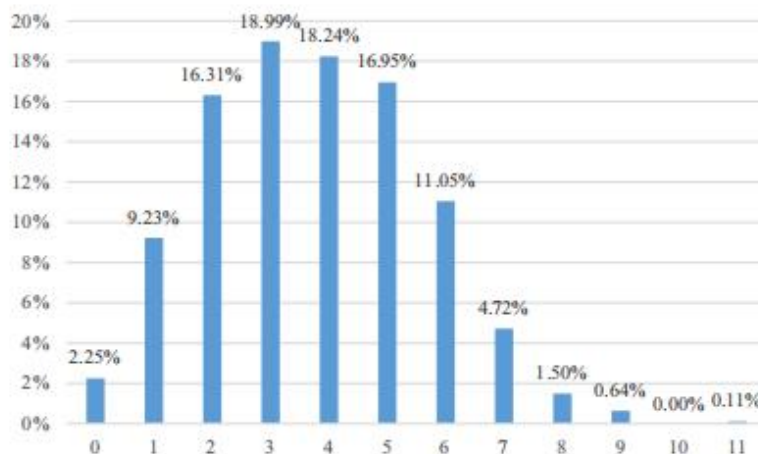
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### 2.3 Descriptive statistics

**2.3.1 Technology adoption.** The third column of Table 1 shows the adoption rate of technologies. Among the 11 technologies identified for litchi production, the most popular technology is pesticide. In particular, the pesticide adoption rate is 88.2%. Moreover, the most and least popular capital-intensive technologies are pruning (61.9%) and irrigation (4.3%). The adoption rates of tree thinning, girdling, grafting and fertigation are 49%, 59%, 39.5% and 5.7%, respectively. In terms of labor-intensive technology, the adoption rates of flower and fruit thinning are 42.7 and 22.9%, respectively. However, only 0.8 and 1% of surveyed households had used insect-proof nets and bagging, respectively.

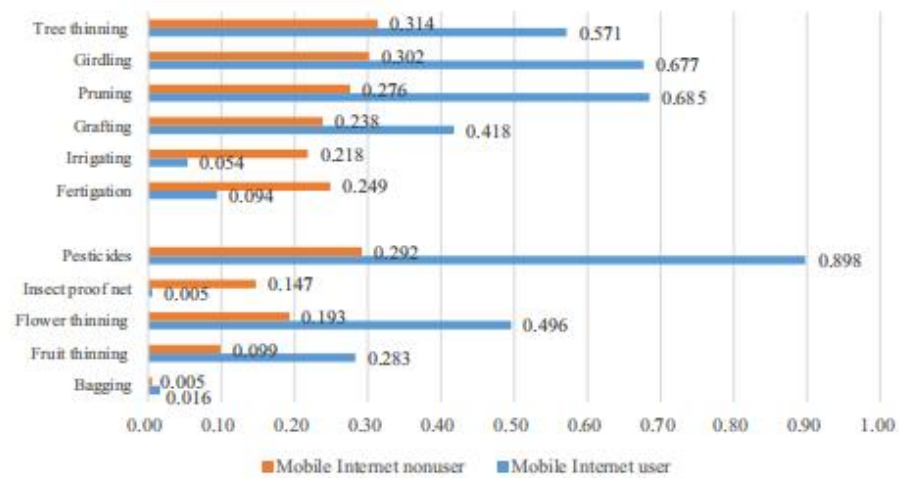
According to Table 2, the mean number of technologies adopted by the 932 sample farmers is 3.749. On average, sample farmers adopted 2.194 capital-intensive technologies and 1.555 labor-intensive technologies. In addition, Figure 1 provides information on the distribution of technology adoption extensity. The results indicate that the majority of the sample farmers had adopted 3 technologies. In particular, 18.99% of the farmers had adopted 3 technologies. Moreover, the percentages of farmers who had adopted 2, 4 and 5 technologies were 16.31%, 18.24% and 16.95%, respectively. Approximately 10% of the farmers had adopted 1 technology or 6 technologies. Only 4.72%, 1.50%, 0.64% and 0.11% of the farmers had adopted 7, 8, 9 and 11 technologies, respectively. However, 2.25% of the farmers had not adopted any technology. In addition, not a single farmer had adopted 10 technologies.

Figure 2 presents information on the technology adoption pattern of mobile Internet users and nonusers. Overall, the treatment and control groups show different technology adoption patterns. In particular, among six capital-intensive technologies, farmers adopting mobile Internet show a larger probability of using grafting, pruning, girdling and tree thinning. The adoption rates of grafting, pruning, girdling and tree thinning for mobile Internet users are 41.8%, 68.5%, 67.7% and 57.1%, respectively. The figures for nonusers are 23.8%, 27.6%, 30.2% and 31.4%, respectively. However, mobile Internet nonusers are found to be more likely to adopt fertigation and irrigation compared to their counterparts. The fertigation and irrigating adoption rates of mobile Internet nonusers are 24.9 and 21.8%, respectively. The figures for mobile Internet users are 9.4 and 5.4%, respectively. For labor-intensive



**Figure 1.**  
The distribution of  
technology adoption  
extensity

**Figure 2.**  
Technology adoption  
patterns of mobile  
Internet users and  
nonusers



technology, the pesticide adoption rate of mobile Internet users is approximately three times that of nonusers. The results also indicate that mobile Internet users are more likely to adopt fruit and flower thinning than farmers who do not use mobile Internet devices. The fruit and flower thinning adoption rates of mobile Internet users are 28.3 and 49.6%, respectively. The figures for nonusers are 9.9 and 19.3%, respectively. Moreover, mobile Internet users rarely adopt bagging and insect-proof net. The adoption rates for bagging and insect-proof net are only 1.6 and 0.5% for mobile Internet users. Similarly, bagging adoption among nonusers is 0.05%. Surprisingly, 14.7% of nonusers have used insect-proof net.

Table 3 provides the results of the mean difference comparisons drawn between the treatment and control groups. The results suggest that the number of technologies, capital-intensive technologies and labor-intensive technologies adopted by mobile Internet

**Table 3.**  
Mean difference  
between mobile  
Internet user and  
nonuser

| Variables                      | Mobile Internet user | Mobile Internet nonuser | Mean difference |
|--------------------------------|----------------------|-------------------------|-----------------|
| All 11 technologies            | 4.197 (1.892)        | 3.453 (1.781)           | 0.744***        |
| Capital-intensive technology   | 2.499 (1.370)        | 1.993 (1.297)           | 0.506***        |
| Labor-intensive technology     | 1.698 (0.927)        | 1.460 (0.849)           | 0.238***        |
| Gender                         | 0.871 (0.336)        | 0.907 (0.290)           | -0.037*         |
| Age                            | 49.16 (9.040)        | 62.17 (8.832)           | -13.018***      |
| Education level                | 9.461 (2.415)        | 7.592 (3.027)           | 1.869***        |
| Health status                  | 0.844 (0.412)        | 0.665 (0.553)           | 0.179**         |
| Farming experience             | 21.06 (9.921)        | 24.130 (10.440)         | -3.065***       |
| Farm size                      | 21.21 (48.430)       | 11.200 (19.410)         | 10.017***       |
| Labor                          | 3.933 (1.597)        | 3.916 (1.970)           | 0.016           |
| Share of litchi farming income | 39.890 (34.140)      | 40.530 (35.730)         | -0.636          |
| Guidebook use                  | 0.237 (0.426)        | 0.191 (0.393)           | 0.046*          |
| Cadre or party membership      | 0.288 (0.454)        | 0.178 (0.383)           | 0.110***        |
| Off-farm work                  | 0.299 (0.459)        | 0.103 (0.305)           | 0.196***        |
| Training                       | 0.650 (0.478)        | 0.510 (0.500)           | 0.140***        |
| Cooperative membership         | 0.305 (0.461)        | 0.267 (0.443)           | 0.037           |
| N                              | 371                  | 561                     | 932             |

Note(s): (1) \*, \*\* and \*\*\* denote significance at 10%, 5% and 1% levels

users is significantly higher than for nonusers (see the top three rows of Table 3). In particular, mobile Internet users and nonusers adopt 4.197 and 3.453 technologies on average, respectively. On average, farmers who adopt mobile Internet have adopted 2.499 capital-intensive technologies and 1.698 labor-intensive technologies. The figures for those not adopting mobile Internet are 1.993 and 1.460, respectively.

**2.3.2 Household characteristics** Table 2 provides definitions and descriptive statistics for the treatment and control variables. The results show that the mobile Internet adoption rate is approximately 40%. In other words, nearly 40% of the sample farmers used mobile Internet. Moreover, most of the household heads are male (89.3%). On average, the age and education level of the sample farmers are 56.99 and 8.336, respectively. Moreover, the average farm size covers 15.180 mu. On average, litchi farming revenue contributes approximately 40% of total household income. In addition, 18.1%, 56.5% and 28.2% of the surveyed farmers have access to off-farm work, training and cooperative membership.

The mean comparison results shown in Table 3 indicate that mobile Internet users differ from their counterparts on some observed characteristics. In particular, mobile Internet users are younger than nonusers. Moreover, mobile Internet users are better educated. In particular, mobile Internet users have 9.461 years of education on average while the figure for nonusers is 7.592. Mobile Internet users also have better health and financial conditions than nonusers. In addition, cadre and party members, off-farm workers and training participants are more likely to adopt mobile Internet. These findings indicate the potential existence of self-selection bias in farmers' decisions regarding mobile Internet adoption.

### 3. Estimation strategy

#### 3.1 Count data model selection

The aim of this research is to examine the effects of mobile Internet adoption on technology adoption extensity. As mentioned in the previous section, the technologies selected have their unique values, and they are the most effective solutions for the problems that arise in different stages of litchi production. In this regard, the outcome variables are count variables. In particular, we identified 11 technologies for farmers to choose from. In other words, technology adoption extensity ranges from 0 to 11. Moreover, the extensities of capital- and labor-intensive technology adoption are measured with intervals [0,6] and [0,5], respectively. We use the count model (Cameron and Trivedi, 2009), expressed as follows, for our empirical analysis:

$$Y_i^j = f(X_i, T_i) + e_i \quad (1)$$

where  $Y_i^j$  is the number of technologies ( $j = 1$ ), capital-intensive technologies ( $j = 2$ ) and labor-intensive technologies ( $j = 3$ ) adopted by farmer  $i$ ;  $X_i$  is the vector of variables associated with farmer's decision regarding technology adoption;  $T_i$  denotes mobile Internet adoption status; and  $e_i$  is a random error term.

The Poisson regression model and negative binomial model are the two basic count models used. The Poisson regression model is preferred in the absence of overdispersion for count data. Existing research suggests that the results of a likelihood-ratio test can help justify the selection of the Poisson regression model or negative binomial model for empirical analysis (Cameron and Trivedi, 2009).

#### 3.2 Correction of selection bias

Basic count models can yield unbiased results in situations where there is no endogenous variable. However, previous studies focusing on ICT adoption suggest that ICT applications, such as the Internet and mobile phones, are not randomly assigned to farmers (Khanal and

Mishra, 2016; Martínez-Domínguez and Mora-Rivera, 2020; Leng *et al.*, 2020). In other words, farmers' decisions on mobile Internet adoption may be affected by both observed (e.g. gender, age, education level and wealth) and unobserved characteristics (e.g. motivation and abilities). Basic count models will produce biased results when selection bias exists.

After confirming the Poisson regression model is more preferred in our case (see Section 4.1 and Table A2 for more information), we select the ETPR model to conduct rigorous estimations. Compared to the Poisson regression model, the ETPR model requires the inclusion of at least one instrumental variable for model identification (Stata, 2019). It thus allows the ETPR model to provide an unbiased result by taking both observed and unobserved characteristics into account.

The ETPR model involves two steps. The first step involves estimating farmers' decisions surrounding mobile Internet adoption. Assume that  $T_i^*$  is the utility difference between farmer  $i$  adopting mobile Internet device ( $U_i^T$ ) and not adopting mobile Internet device ( $U_i^{nT}$ ). Farmer  $i$  will apply the mobile Internet device only when  $T_i^* = U_i^T - U_i^{nT} > 0$ . Considering that we can only observe farmer's mobile Internet adoption status ( $T_i$ ) from the field survey, utility difference  $T_i^*$  can alternatively be expressed as the follows:

$$T_i^* = \alpha Z_i + \mu_i, \quad T_i = \begin{cases} 1 & \text{if } U_i^T - U_i^{nT} > 0 \\ 0 & \text{if } U_i^T - U_i^{nT} \leq 0 \end{cases} \quad (2)$$

where  $T_i = 1$  if farmer  $i$  adopts mobile Internet and  $T_i = 0$  otherwise;  $Z_i$  is the vector of variables associated with farmer's decision regarding mobile Internet adoption;  $\alpha_i$  is a vector of parameters to be estimated; and  $\mu_i$  is a random error term.

The impact of mobile Internet adoption on technology adoption extensity (Eqn. 1) is estimated in the second step of the ETPR model. For model identification, we include the message variable, which serves as the instrumental variable, in  $Z_i$ . As indicated by Penard *et al.* (2015), individuals who are able to install and use computer software are more likely to use the Internet. In this regard, mobile phone-savvy farmers are assumed to show a greater probability of using the mobile Internet. Evidence suggests that Chinese smallholder farmers benefit from the Internet use for alleviating information asymmetry, which facilitates technology adoption (Ma and Wang, 2020). Moreover, the average age of household head is 57 and they received an average of 8 years of education. In other words, they rarely received any ICT training during the school year. From field survey we found that mobile Internet users only have basic ICT skills, and their ICT use is limited to communication (e.g. making phone call and sending WeChat message) and entertainment (e.g. watching online video and playing games). Farmers rarely apply ICTs for human capital-enhancing activities, such as online education and healthcare, due to the lack of digital skills, digital awareness, infrastructure and social support. They also have trust issues in Internet information. Instead of digging online information by their own, mobile Internet users can easily obtain technology guidance from people who they are familiar with (e.g. local agricultural extension workers, agricultural cooperative members and village cadres) by entering WeChat group. In addition, the technologies selected in this study do not require any digital skills and knowledge. In this regard, the message variable only affects the surveyed farmers' technology adoption via using the mobile Internet.

## 4. Results and discussions

### 4.1 Count model selection

We first run likelihood-ratio tests to determine whether the Poisson regression model or negative binomial model is preferred in our case. The likelihood test results presented in Table A2 show that  $p$ -values are not significant in evaluating the effects of mobile Internet

adoption on the number of technologies, capital-intensive technologies and labor-intensive technologies adopted by farmers, which suggest that the outcome variables are not over-dispersed. Therefore, the Poisson regression model is preferred.

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#### 4.2 ETPR model and Poisson regression model selection

After confirming the use of the Poisson regression model as the basic count model, we use the ETPR model to address potential endogeneity problems. Table 4 presents the results of both the ETPR model and Poisson regression model. The estimated correlation between the treatment-assignment errors and outcome errors  $\rho$  is positive and significant (see the bottom of the second column). This confirms the existence of positive selection bias. In other words, the impact of mobile Internet adoption on technology adoption extensity would be overestimated if selection bias were not properly addressed. As shown in the first row of Table 4, the IRR value of mobile Internet adoption estimated using the ETPR model is lower than that of the Poisson regression model. We further discuss the economic meaning of these results in the following subsections.

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| Variables                      | Mobile Internet adoption (Coef.) | ETPR model Technology adoption extensity (Coef.)   | Technology adoption extensity (IRRs) | Poisson regression model Technology adoption extensity (IRRs) |
|--------------------------------|----------------------------------|----------------------------------------------------|--------------------------------------|---------------------------------------------------------------|
| Mobile Internet adoption       |                                  | 0.115*** (0.044)                                   | 1.122*** (0.049)                     | 1.144*** (0.045)                                              |
| Gender                         | 0.012 (0.185)                    | -0.084 (0.052)                                     | 0.920 (0.048)                        | 0.919 (0.048)                                                 |
| Age                            | -0.074*** (0.009)                | -0.001 (0.002)                                     | 0.999 (0.002)                        | 0.999 (0.002)                                                 |
| Education level                | 0.065** (0.032)                  | 0.009* (0.006)                                     | 1.009* (0.006)                       | 1.009 (0.006)                                                 |
| Health status                  | -0.138 (0.131)                   | 0.021 (0.038)                                      | 1.021 (0.039)                        | 1.022 (0.039)                                                 |
| Off-farm work                  | 0.186 (0.122)                    | -0.043 (0.046)                                     | 0.958 (0.044)                        | 0.948 (0.043)                                                 |
| Training                       | 0.392*** (0.115)                 | 0.072* (0.040)                                     | 1.074* (0.043)                       | 1.072* (0.043)                                                |
| Farm year                      | -0.003 (0.007)                   | 0.002 (0.001)                                      | 1.002 (0.001)                        | 1.002 (0.001)                                                 |
| Share of litchi farming income | -0.001 (0.002)                   | 0.002*** (0.001)                                   | 1.002*** (0.001)                     | 1.002*** (0.001)                                              |
| Farm size                      | 0.005** (0.002)                  | 0.001** (0.000)                                    | 1.001** (0.000)                      | 1.001** (0.000)                                               |
| Labor                          | 0.081** (0.035)                  | 0.001 (0.009)                                      | 1.001 (0.009)                        | 1.001 (0.009)                                                 |
| Guidebook use                  | -0.076 (0.137)                   | 0.085** (0.042)                                    | 1.089** (0.046)                      | 1.088** (0.046)                                               |
| Cadre or party membership      | 0.202 (0.145)                    | -0.019 (0.040)                                     | 0.981 (0.039)                        | 0.980 (0.039)                                                 |
| Cooperative membership         | 0.027 (0.103)                    | 0.072** (0.034)                                    | 1.075** (0.037)                      | 1.075** (0.037)                                               |
| Yulin                          | -0.164 (0.214)                   | -0.324*** (0.086)                                  | 0.723*** (0.062)                     | 0.724*** (0.062)                                              |
| Qinzhou                        | -0.426*** (0.132)                | -0.103** (0.052)                                   | 0.902** (0.047)                      | 0.904* (0.047)                                                |
| Beihai                         | -0.476*** (0.179)                | -0.308*** (0.097)                                  | 0.735*** (0.072)                     | 0.737*** (0.071)                                              |
| Maoming                        | 0.450*** (0.119)                 | -0.077 (0.074)                                     | 0.926 (0.069)                        | 0.924 (0.068)                                                 |
| Shenzhen                       | 0.262 (0.234)                    | -0.074 (0.077)                                     | 0.929 (0.071)                        | 0.927 (0.071)                                                 |
| Message                        | 1.893*** (0.130)                 |                                                    |                                      |                                                               |
| Constant                       | 1.671*** (0.528)                 | 1.224*** (0.136)                                   | 3.401*** (0.464)                     | 3.306*** (0.431)                                              |
| $\rho$                         | 1.632*** (0.226)                 |                                                    |                                      |                                                               |
| Wald test( $\rho=0$ )          |                                  | $\chi^2(1) = 52.25, \text{Prob} > \chi^2 = 0.0000$ |                                      |                                                               |
| Observations                   | 932                              |                                                    | 932                                  |                                                               |

Note(s): (1) \*, \*\* and \*\*\* denote significance at 10%, 5% and 1% levels. (2) Reference region: Zhanjiang. (3) Standard errors in parentheses. (4) Standard errors adjusted for 40 clusters by village

**Table 4.**  
ETPR model and Poisson regression model results

#### 4.3 Determinants of mobile Internet use

The first stage of the ETPR model estimates the factors that influence farmers' decisions regarding mobile Internet adoption. The second column of Table 4 suggests that mobile Internet adoption is positively associated with education level, training participation, farm size and labor but negatively related to household head age. Overall, our findings confirm that mobile Internet adoption is not randomly assigned among farmers. This finding is consistent with a large amount of existing literature (Penard *et al.*, 2015; Martínez-Domínguez and Mora-Rivera, 2020; Tadesse and Bahigwa, 2015). However, mixed results are found on the impact of a certain variable on ICT adoption. For example, using household survey data from Cameroon, Penard *et al.* (2015) find that males have a larger probability of adopting the Internet. Another study suggests that the probability of Internet use is higher for women in rural Mexico (Martínez-Domínguez and Mora-Rivera, 2020). In our case, we find no significant impact of gender on mobile Internet adoption. Moreover, we find a significant impact of the location fixed effect. In particular, compared to Zhanjiang farmers, farmers from Qin Zhou and Beihai are less likely to adopt mobile Internet devices while farmers show a higher probability of adopting them. In addition, the message variable serves as an instrumental variable in the ETPR model. The results suggest that mobile phone-savvy farmers are more likely to adopt mobile Internet devices.

#### 4.4 Determinants of technology adoption extensity

The third column of Table 4 provides the variable coefficients estimated using the ETPR model. Since the variable coefficients of the count model cannot be directly interpreted (Cameron and Trivedi, 2009), the incidence rate ratio (IRR) of variables is further calculated and presented in the fourth column of Table 4. For purposes of comparison, the IRRs estimated using the Poisson regression model are presented in the last column of Table 4. In addition, the variable coefficients estimated using the Poisson regression model can be found in Table A3.

In terms of the variable of interest, the ETPR model result shows that the estimated coefficient of mobile Internet adoption is positive and the IRR is greater than 1. This suggests that mobile Internet adoption has a positive impact on the number of technologies adopted by farmers. In particular, on average, mobile Internet users adopt 1.122 times (or 12.2%) more technologies than nonusers. Mobile Internet use facilitates information flow between litchi growers and agricultural extension service workers, agricultural cooperative members, village cadres and elite litchi producers. The potential mechanism of the treatment is that mobile Internet users are increasingly aware of the benefits of the technologies. Moreover, they can receive timely tailored recommendations for technology application, which helps increase adoption rates.

The last column of Table 4 gives the IRR estimated using the Poisson regression model. The result suggests that farmers who adopt mobile Internet apply 1.144 times (or 14.4%) more technologies than nonusers. Clearly, the Poisson regression model overestimates the impact of mobile Internet adoption on technology adoption extensity without taking unobserved factors into account.

In addition to mobile Internet adoption, the ETPR model results suggest that factors including education level, training, share of litchi farming income, guidebook use and cooperative membership affect farmers' decisions regarding the number of technologies adopted. In particular, the IRR for education level is greater than 1 and statistically significant. It suggests that farmers who are better educated use more technologies. Training participants and cooperative members respectively adopt 7.4 and 8.9% more technologies than their counterparts. It may be that training and cooperative participation are the main channels through which farmers access modern technologies. Farmers often learn about modern technologies from agricultural extension workers through training. Moreover, farmer cooperatives are also responsible for promoting new technologies in rural China. We

find that farmers who have a larger share of litchi farming income adopt 0.2% more technologies than their counterparts. This result suggest that farmers who are more reliant on litchi farming tend to adopt more technologies. In addition, a positive and statistically significant IRR for guidebook use indicates that farmers who follow the official production guidelines may be more aware of standard litchi production and thus more likely to use more technologies. We also find a location fixed effect on the extensity of technology adoption. Relative to farmers living in Zhanjiang, those living in Yulin, Qinzhou and Beihai adopt 27.7%, 9.8% and 26.5% fewer technologies, respectively.

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#### 4.5 Disaggregated analyses

The 11 technologies identified for litchi production are further divided into 6 capital-intensive technologies and 5 labor-intensive technologies. Table 5 presents the results of disaggregated analyses. We find from the bottom of the second and fourth columns of Table 5 that the coefficients of  $\rho$  are positive and statistically significant. This finding indicates the existence of positive selection bias in estimating the effects of mobile Internet adoption on both capital- and labor-intensive technology adoption extensity. The third and fifth columns of Table 5 present the IRR results of the determinants of capital- and labor-intensive technology

|                                      | Mobile Internet<br>adoption (Coef.)            | Capital-intensive<br>technology adoption<br>extensity (IRRs) | Mobile Internet<br>adoption (Coef.)          | Labor-intensive<br>technology adoption<br>extensity (IRRs) |
|--------------------------------------|------------------------------------------------|--------------------------------------------------------------|----------------------------------------------|------------------------------------------------------------|
| Mobile Internet<br>adoption          |                                                | 1.141*** (0.055)                                             |                                              | 1.104** (0.054)                                            |
| Gender                               | 0.013 (0.185)                                  | 0.970 (0.067)                                                | 0.009 (0.186)                                | 0.857*** (0.045)                                           |
| Age                                  | -0.074*** (0.009)                              | 0.998 (0.002)                                                | -0.074*** (0.009)                            | 1.000 (0.002)                                              |
| Education level                      | 0.065** (0.032)                                | 1.016** (0.008)                                              | 0.065** (0.032)                              | 1.000 (0.007)                                              |
| Health status                        | -0.138 (0.131)                                 | 1.027 (0.048)                                                | -0.139 (0.129)                               | 1.014 (0.037)                                              |
| Off-farm work                        | 0.186 (0.122)                                  | 0.939 (0.056)                                                | 0.185 (0.121)                                | 0.987 (0.049)                                              |
| Training                             | 0.393*** (0.115)                               | 1.096* (0.057)                                               | 0.392*** (0.116)                             | 1.045 (0.044)                                              |
| Farm year                            | -0.003 (0.007)                                 | 1.003* (0.002)                                               | -0.004 (0.007)                               | 1.001 (0.002)                                              |
| Share of litchi<br>farming<br>income | -0.001 (0.002)                                 | 1.002*** (0.001)                                             | -0.001 (0.002)                               | 1.001** (0.001)                                            |
| Farm size                            | 0.005** (0.002)                                | 1.001*** (0.000)                                             | 0.005** (0.002)                              | 1.000 (0.000)                                              |
| Labor                                | 0.081** (0.035)                                | 0.998 (0.011)                                                | 0.081** (0.034)                              | 1.005 (0.010)                                              |
| Guidebook use                        | -0.075 (0.138)                                 | 1.078 (0.058)                                                | -0.075 (0.136)                               | 1.104** (0.049)                                            |
| Cadre or party<br>membership         | 0.202 (0.145)                                  | 1.010 (0.058)                                                | 0.201 (0.143)                                | 0.939 (0.037)                                              |
| Cooperatives<br>membership           | 0.026 (0.103)                                  | 1.081* (0.044)                                               | 0.025 (0.103)                                | 1.068 (0.047)                                              |
| Yulin                                | -0.166 (0.215)                                 | 0.724*** (0.086)                                             | -0.162 (0.213)                               | 0.721*** (0.044)                                           |
| Qinzhou                              | -0.427*** (0.199)                              | 0.948 (0.048)                                                | -0.423** (0.133)                             | 0.840*** (0.058)                                           |
| Beihai                               | -0.477*** (0.179)                              | 0.743** (0.097)                                              | -0.471** (0.177)                             | 0.724*** (0.045)                                           |
| Maoming                              | 0.448*** (0.119)                               | 0.834** (0.068)                                              | 0.448** (0.119)                              | 1.039 (0.088)                                              |
| Shenzhen                             | 0.261 (0.234)                                  | 0.873* (0.071)                                               | 0.258 (0.232)                                | 1.009 (0.091)                                              |
| Message                              | 1.895*** (0.130)                               |                                                              | 1.894*** (0.130)                             |                                                            |
| Constant                             | 1.665*** (0.528)                               | 1.801*** (0.300)                                             | 1.655*** (0.523)                             | 1.600*** (0.224)                                           |
| $\rho$                               | 1.662*** (0.196)                               |                                                              | 1.397*** (0.522)                             |                                                            |
| Wald test( $\rho=0$ )                | $\chi^2(1) = 71.56$ , Prob > $\chi^2 = 0.0000$ |                                                              | $\chi^2(1) = 7.17$ , Prob > $\chi^2 = 0.007$ |                                                            |
| Observations                         | 932                                            |                                                              | 932                                          |                                                            |

Note(s): (1) \*, \*\* and \*\*\* denote significance at 10%, 5% and 1% levels. (2) Reference region: Zhanjiang. (3) Standard errors in parentheses. (4) Standard errors adjusted for 40 clusters by village

Table 5.  
Disaggregated  
analyses results

adoption extensity. In addition, the variable coefficients estimated using the ETPR model can be found in [Table A3](#).

In terms of the determinants of capital-intensive technologies, the IRR results suggest that mobile Internet adoption increases the average number of capital-intensive technologies adopted by 14.1%. In addition to mobile Internet adoption, the IRRs for education level, training, farm year, share of litchi farming income, farm size and cooperative membership are greater than 1 and statistically significant. These results suggest that farmers who are better educated, have more farming experience, participate in training and cooperatives, are more reliant on litchi farming and have larger farms adopt more capital-intensive technologies. Moreover, farmers from Yulin, Beihai, Maoming and Shenzhen adopt 27.6%, 25.7%, 16.6% and 12.7% fewer capital-intensive technologies than those from Zhanjiang (reference region).

Regarding the determinants of labor-intensive technologies, the IRR result presented in the fifth column confirms the positive role of mobile Internet adoption in the extensity of labor-intensive technology adoption. On average, mobile Internet users adopt 10.4% more labor-intensive technologies than those who do not adopt mobile Internet devices. Compared to male farmers, female farmers adopt 14.3% fewer labor-intensive technologies. Moreover, the findings show that the variables, including share of litchi farming income and guidebook use, are positively and significantly associated with the extensity of labor-intensive technology adoption. In addition, compared to farmers living in Zhanjiang (reference region), those living in Yulin, Qinzhou and Beihai adopt 27.9%, 16% and 27.6% fewer labor-intensive technologies.

Interestingly, upon combining the estimated IRRs for mobile Internet adoption on the number of capital- and labor-intensive technologies adopted by farmers, we find that mobile Internet use has a greater impact in facilitating the spread of capital-intensive technologies among farmers. It may be that rural farmers can easily access the tools required for labor-intensive technologies at local grocery stores and from the agricultural input market. In most cases, the basic tools required for labor-intensive technologies are less expensive. Moreover, labor-intensive technology is less complicated than capital-intensive technology. In this regard, some labor-intensive technologies can easily spread through existing rural social networks. For example, the purpose of fruit, tree and flower thinning is to make room for the growth of other plants or trees. Litchi farmers can easily purchase scissors and ladders to remove flower clusters and small and shaded fruitlets. However, tree thinning always requires the use of specialized machines. Farmers can either purchase such machines on their own or contact external technology suppliers. The use of mobile Internet can reduce the transaction costs of tree thinning by reducing information search costs and facilitating communication between farmers and external service suppliers.

## 5. Conclusion

Based on household survey data, this study uses an ETRP model to examine the effect of mobile Internet adoption on technology adoption extensity. Our empirical results show that mobile Internet adoption can encourage farmers to adopt more technologies. In addition to mobile Internet adoption, the extensity of technology adoption is determined by education level, training, share of litchi farming income, guidebook use, cooperative membership and location fixed effects. The results of disaggregated analyses further confirm the positive role of mobile Internet adoption in both capital- and labor-intensive technology adoption extensity. Interestingly, we find that the adoption of mobile Internet has a greater impact on the extensity of capital-intensive technology adoption than on the extensity of labor-intensive technology adoption.

Our findings have several policy implications. To further promote agricultural technology adoption, policymakers should make efforts to improve the availability, connectivity and affordability of mobile Internet for rural households. In particular, governments may collaborate

with telecommunication companies to expand the coverage of mobile Internet services, improve the speed and stability of services and lower service fees. Smartphone is the basic device required for a farmer to connect to the mobile Internet. In this regard, policymakers can work with mobile device suppliers to provide rural households with suitable contracts. Moreover, the provision of agricultural extension services, such as training opportunities and guidebooks, could enhance the penetration of agricultural technologies. In addition, encouraging farmers to participate in agricultural cooperation can help promote technology adoption.

Although this study is limited to Guangxi and Guangdong, our findings may have implications for other litchi producing areas, which are mainly concentrated in tropical areas of southern Asia. Moreover, we find evidence of a positive impact of ICT use on agricultural technology adoption. This study can thus guide the design of policies aimed to promote agricultural technologies through the use of ICT.

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# E-commerce participation, digital finance and farmers' income

E-commerce participation

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## Abstract

**Purpose** – It is imperative to achieve sustainable growth in farmers' earnings to sustain poverty alleviation efforts and achieve rural revitalization goals. The authors investigated the nature of the non-linear relationship between farmers' e-commerce participation and income growth, analyzed the rationale behind this correlation and examined the moderating effect of digital finance on this relationship.

**Design/methodology/approach** – The authors conducted an empirical investigation using rural household data from the China Household Finance Survey and the regional digital finance index compiled by Peking University. The authors employed a fixed-effect model and a moderating effect model to identify the non-linear influences of e-commerce participation on farmers' income and to analyze the positive synergies of digital finance. The authors used identification and estimation techniques to mitigate the endogeneity problem, specifically employing heteroscedasticity-based instruments.

**Findings** – There is an inverted U-shaped relationship between e-commerce participation and farmers' income. Digital finance reduces the declining trend in the marginal effects of e-commerce and increases marginal values. Furthermore, the synergistic effect can promote the quality and efficiency of business activities by easing credit constraints, reducing risk aversion and stimulating innovative activities, which in turn can lead to sustained revenue growth.

**Originality/value** – Few studies have focused on the non-linear relationship between e-commerce and farmers' income. This implies that achieving sustained income growth using e-commerce alone is difficult. The synergy between e-commerce and digital finance is a feasible path for achieving this goal.

**Keywords** E-commerce participation, Farmer's income, Digital finance, Synergy

**Paper type** Research paper

## 1. Introduction

Continual income growth for underprivileged strata has been a shared objective of developing nations and is intricately linked to the stability and progress of society (Rothstein and Uslaner, 2005; Benjamin *et al.*, 2011). In China, approximately 770 million rural residents constitute 54.6% of the overall population; their per capita disposable income was \$2,995.63 in 2022, with the ratio of per capita disposable income between rural and urban residents being 2.5, signifying a substantial discrepancy 1 and 2. The Chinese government has introduced a series of policies in the past decade to help farmers move from poverty to prosperity, including the development of rural e-commerce, which was once listed as one of the ten targeted poverty alleviation projects to be implemented nationwide and is now an important driver of rural revitalization (Feng and Zhang, 2022; Li and Qin, 2022). However,



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online marketing costs have surged. Some villages experienced a decline in online sales. Village names have even disappeared from the national Taobao Village list. The revenue-raising effect of e-commerce participation slowed. However, only a few studies have focused on this aspect. To verify the non-linear relationship between e-commerce participation and income, we broadly divided the development of rural e-commerce in China into three stages—initial, expansion and self-renewal—with reference to [Leong et al. \(2016\)](#). Corresponding to the different development stages, farmers' income from e-commerce participation changes.

In the initial stage of rural e-commerce development, an e-commerce ecosystem centered on e-commerce platforms gradually emerged in response to rising online demand ([Leong et al., 2016](#)). The use of e-commerce allows farmers to bypass middlemen and transact with customers without leaving their homes, thus reducing transaction costs. Furthermore, farmers have access to timely and accurate market information through e-commerce, reducing information costs and mitigating efficiency losses and the erosion of farmers' bargaining position ([Jensen, 2007](#)). Thereby, the initial phase of rural e-commerce development was characterized by a significant increase in farmers' household incomes ([Peng et al., 2021](#)).

During the expansion stage of rural e-commerce, villagers participating in e-commerce had access to better Internet, logistics and e-supply chain services. In addition to selling agricultural products online, smallholders have the opportunity to integrate into the e-commerce supply chain by participating in e-commerce production and service activities such as production, packaging, distribution and grading. In this stage, the e-commerce ecosystem evolves from growth to maturity, and farmers diversify the ways they can earn income by participating in e-commerce ([Leong et al., 2016](#)).

During the self-renewal stage of rural e-commerce development, competition intensifies between e-commerce platforms and the ecosystems dominated by these platforms. Competition also increases among telecommunications, logistics and supply chain service companies. The number of online retailers grows rapidly because capital barriers to e-commerce entry are low. To protect consumer rights and maintain market order, e-commerce platforms have imposed stricter regulations on merchants ([Ferrante, 2015](#)). The income divergence effect of e-commerce skills is emerging in an increasingly competitive environment. The human capital constraints of farmers slow income growth. In addition, farmers have limited innovation capacity, and they often imitate each other, resulting in increased homogenized competition. They have difficulty maintaining their online reputation in the face of infringement disputes and negative consumer reviews. Finally, farmers may feel complacent after experiencing income growth and unwilling to take the risk of innovation, thereby reducing their motivation to engage in skills training. Both objective and subjective factors constrain farmers' innovative activities, forcing them to rely on continuous price reductions to maintain market share, ultimately leading to excessive competition. Excessive competition can trigger negative externalities. Evidence from the town of Zeguo in Zhejiang, China suggests that new e-commerce entrants to the local shoe industry have increased labor and land costs while also disrupting product prices ([Tang and Zhu, 2020](#)). There is an inverted U-shaped relationship between economic agglomeration and farmers' incomes in Taobao Villages. Thus, we formulated the following hypothesis:

- H1. E-commerce participation and farmers' income exhibit an inverted U-shaped relationship.*

The popular application of the Internet and smartphones has promoted the development of rural e-commerce while also enhancing the level of financial inclusion. In the self-renewal stage of rural e-commerce, the demand for capital from business entities rises due to expanding competition. At this time, digital finance can regulate rural e-commerce income in the following three ways so that income in the phase of diminishing marginal effects does not decline rapidly.

- (1) *Increasing opportunities to obtain credit.* The funding needs of e-commerce participants are generally characterized by high liquidity and short lead times (mostly 1–3 months), as well as urgent time requirements for the use of withdrawals and high requirements for facilitation. Rural banks often have lengthy credit approval processes, and credit products are generally based on one-year loans, which are difficult to match with the temporary, urgent and short-term needs of e-commerce operators. The development of digital finance can effectively alleviate the credit constraints of e-commerce participants and meet rapid and flexible capital needs (Xu *et al.*, 2022). Sufficient funds can help rural online retailers avoid being eliminated from market competition and provide a guarantee for business transformation and upgrading, thereby alleviating the downward trend in their income.
- (2) *Improving farmers' risk-taking.* Household risk aversion can severely constrain households from participating in financial markets and optimizing asset allocation (Duan and Cui, 2016). With the further penetration of digital finance in rural areas, farmers have frequently begun to use digital functions (such as mobile payments and online shopping). As households become accustomed to efficient services and rich products of digital finance, their risk aversion will drop and their risk tolerance level will rise (Hong *et al.*, 2021), thus motivating households to participate more often in risky financial markets. Changes in risk attitudes can enhance farmers' ability to withstand pressure and adapt to changes, enabling them to survive in a fiercely competitive environment.
- (3) *Support for innovation activities.* Innovation is a viable path for exiting a competitive quagmire. Innovation is subject to uncertainty and a certain amount of time for technology incubation and time-to-market (Bessant, 2008; Townsend *et al.*, 2018; Islam *et al.*, 2020), so enterprises need adequate funding and personnel to keep innovation activities running (Wellalage and Fernandez, 2019). Digital financing provides rural business entities with the possibility of innovating products and services. On the consumption side, digital finance reduces the cost of financial services for consumers, improves the spatial and temporal allocation of credit resources and increases the quantity and quality of resident consumption (Li *et al.*, 2020). Consumption in the long-tail market is effectively exploited, indicating the direction of product and service innovations. Second, from the supply side, digital finance weakens the information asymmetry between firms and investors in the financial market (Berg, 2020), enabling the precise matching of supply and demand for innovation funds and improving the efficiency of innovation financing (Teece, 2009). This situation enriches innovative financing channels, accelerates bank credit approval (Fuster *et al.*, 2019) and reduces the cost of innovation financing for firms. Finally, the development of digital finance has reconstructed the distributed business model, which facilitates the communication, cooperation and collaborative development of innovation entities in the distributed innovation network. As such, we formed the following hypotheses:

H2. Digital finance positively moderates the inverted U-shaped relationship between e-commerce participation and farmers' incomes.

### 3. Data, descriptive analysis and econometric models

#### 3.1 Data

The dataset was selected from three sources. First, we used three waves of data (2015, 2017 and 2019) from the China Household Finance Survey (CHFS), a national longitudinal survey focused on the study of household economic and financial behavior. We chose the rural

households engaged in business activities as our sample to analyze the impact of e-commerce participation on household income. To measure e-commerce participation, we primarily utilized the ratio of individuals employed in e-commerce activities (including both internal household members and external employees) to the total household size. As household sizes vary, we used relative values to assess the level of participation. Second, the index of digital finance in China was used to measure the development of digital finance at the provincial level. This index is guided by Peking University and has been compiled in two periods, covering the years 2010–2021. Third, we compiled information from the China Statistical Yearbook to obtain provincial indicators on the level of economic development. Finally, the micro and macro data were matched together in 2015, 2017 and 2019. After excluding samples with missing key variables, a total of 8,043 samples were used.

### 3.2 Description of focus variable

The explanatory variable *Income* is primarily measured as the logarithm of per capita household income. Table 1 provides an overview of the variables and their summary statistics. The *Gender* variable reflects the gender of household heads. The CHFS database defines “household heads” as the main breadwinner of the household or the main director. Our study follows this definition. The average age of the household head is 49 years, with the

| Variables              | Definition                                                 | Mean    | SD     | Min.   | Max.   |
|------------------------|------------------------------------------------------------|---------|--------|--------|--------|
| <i>Lnpincome</i>       | Per capita household income (log)                          | 9.338   | 1.689  | 0      | 12.802 |
| <i>Employ</i>          | Number of employees in e-commerce projects/<br>Family size | 0.074   | 1.043  | 0      | 75.5   |
| <i>DFT</i>             | Total digital finance Index/100                            | 2.351   | 0.518  | 1.459  | 3.777  |
| <i>Cover</i>           | Coverage width/100                                         | 2.19    | 0.492  | 1.392  | 3.539  |
| <i>Usage</i>           | Depth of use/100                                           | 2.205   | 0.616  | 1.073  | 4.004  |
| <i>Digit</i>           | Degree of digitization/100                                 | 3.151   | 0.557  | 2.307  | 4.403  |
| <i>Age</i>             | Age of head of household                                   | 49.233  | 11.915 | 19     | 95     |
| <i>Age<sup>2</sup></i> | Squared age of head of household                           | 25.658  | 12.149 | 3.61   | 90.25  |
| <i>Gender</i>          | 1 = Household head is male; 0 = female                     | 0.856   | 0.351  | 0      | 1      |
| <i>Married</i>         | 1 = in marriage; 0 = other                                 | 0.93    | 0.256  | 0      | 1      |
| <i>Health</i>          | 1 = healthy; 0 = other                                     | 0.892   | 0.31   | 0      | 1      |
| <i>Edu</i>             | 1 = Educated to high school level and beyond;<br>0 = other | 0.245   | 0.43   | 0      | 1      |
| <i>Family size</i>     | Number of family members                                   | 4.016   | 1.656  | 1      | 16     |
| <i>Childp</i>          | Proportion of children                                     | 0.187   | 0.183  | 0      | 0.75   |
| <i>Oldp</i>            | Proportion of the elderly                                  | 0.145   | 0.247  | 0      | 1      |
| <i>Pro_lnpgdp</i>      | Per capita GDP at provincial level(log)                    | 10.879  | 0.377  | 10.135 | 11.989 |
| <i>Pro_uratio</i>      | Provincial urbanization rate                               | 0.578   | 0.086  | 0.382  | 0.938  |
| <i>Pro_jobless</i>     | Provincial unemployment rate (urban) *100                  | 3.22    | 0.574  | 1.3    | 4.5    |
| <i>Pro_phone</i>       | Provincial mobile phone penetration rate                   | 103.802 | 22.843 | 64.69  | 189.46 |
| <i>Pro_consumption</i> | Provincial rural-urban consumption gap                     | 0.485   | 0.052  | 0.371  | 0.592  |
| <i>Ln debt</i>         | Household debt (log)                                       | 6.473   | 5.659  | 0      | 16.323 |
| <i>Debt_bank</i>       | 1 = Have a bank loan; 0 = other                            | 0.086   | 0.281  | 0      | 1      |
| <i>Debt_infor</i>      | 1 = Have a private loan; 0 = other                         | 0.129   | 0.335  | 0      | 1      |
| <i>Debt_net</i>        | 1 = Have an Internet loan; 0 = other                       | 0.012   | 0.107  | 0      | 1      |
| <i>Lninvest</i>        | Innovation investment funds (log)                          | 0.376   | 1.872  | 0      | 13.998 |
| <i>Risk</i>            | Risk attitude of household <sup>a</sup>                    | 2.012   | 1.178  | 1      | 5      |

Note(s): <sup>a</sup>Risk attitude level: 1 = low, 2 = slightly low, 3 = average, 4 = slightly high, 5 = high. Data source: CHFS2015, 2017, 2019

Source(s): Authors' own work

Table 1.  
Descriptive analysis

majority of the sample having no education beyond high school. The overall health status of the participants is generally good. The average household size is approximately 4 persons and both the child support ratio and elderly support ratio are around 15%. The core independent variables are the relative number of e-commerce projects' employment, the digital finance index (DFI) and their interaction terms.

### 3.3 Econometric model

**3.3.1 E-commerce involvement and household income: an inverted U-shaped test.** To test Hypothesis 1, we used a fixed-effects model to identify the causal relationship between e-commerce participation and household income based on a Chinese household-level perspective. First, the *Employ* and its quadratic term were used as the key explanatory variables. The following regression model is presented:

$$Y_{i,p,t} = \beta_0 + \beta_1 \text{Employ}_{i,p,t} + \beta_2 \text{Employ}_{i,p,t}^2 + X_{i,p,t}'\phi + X_{p,t}'\eta + \alpha_p + \delta_t + \varepsilon_{i,p,t} \quad (1)$$

$Y_{i,p,t}$  is the logarithm of the per capita household income of rural household  $i$  in province  $P$  during year  $t$ ;  $\text{Employ}_{i,p,t}$  is the level of e-commerce participation for household  $i$  and the squared term  $\text{Employ}_{i,p,t}^2$  is also added to test the nonlinear relationship in Hypothesis 1;  $X_{i,p,t}$  is a set of head-of-household and household-level control variables that may affect total household income (e.g. *age*, *age squared*, *education*, *health status* and *household size*);  $X_{p,t}$  is a set of provincial-level control variables (e.g. *GDP per capita*, *unemployment rate* and *ICT infrastructure*);  $\alpha_p$  is a provincial-fixed effect used to control for some provincial-level differences that may impact the income of rural households;  $\delta_t$  is a time-fixed effect to control for unobserved time-varying factors that help identify more accurately the causal relationship between *Employ* and farmer's income;  $\varepsilon_{i,p,t}$  is an error term.

Our main interest in Model (1) lies in the coefficients  $\beta_1$  and  $\beta_2$ . If  $\beta_1$  is positive and significant but  $\beta_2$  is not significant, it indicates a single linear relationship between e-commerce participation and the income of farmer households. However, if  $\beta_1$  is positive and significant, but  $\beta_2$  is negative and significant, this supports Hypothesis 1, which suggests an inverted U-shaped relationship. To account for arbitrary correlation within cities, standard errors were clustered at the city level.

**3.3.2 Testing the moderating effect of the inverted U-shaped relationship.** To examine the moderating effect of digital finance on the inverted U-shaped relationship described above, we used the following model to analyze the marginal impact of e-commerce participation on farmers' household income at a specific level of digital finance:

$$Y_{i,p,t} = \beta_0 + \beta_1 \text{Employ}_{i,p,t} + \beta_2 \text{Employ}_{i,p,t}^2 + \beta_3 \text{Employ}_{i,p,t} \times \text{DFI}_{p,t-1} + \beta_4 \text{Employ}_{i,p,t}^2 \times \text{DFI}_{p,t-1} + \beta_5 \text{DFI}_{p,t-1} + X_{i,p,t}'\phi + X_{p,t}'\eta + \alpha_p + \delta_t + \varepsilon_{i,p,t} \quad (2)$$

where  $Y_{i,p,t}$ ,  $\text{Employ}_{i,p,t}$ ,  $\text{Employ}_{i,p,t}^2$ ,  $X_{i,p,t}$ ,  $X_{p,t}$ ,  $\alpha_p$ ,  $\delta_t$  and  $\varepsilon_{i,p,t}$  carry the same meaning as in Model (1). In contrast to Model (1), we have introduced a new term  $\text{DFI}_{p,t-1}$ , along with its interaction term with  $\text{Employ}_{i,p,t}$  and  $\text{Employ}_{i,p,t}^2$ . This is a standard model setting for examining the moderating effect of an inverted U-shaped relationship. It is worth noting that we have employed a one-year lagged digital finance index ( $\text{DFI}_{p,t-1}$ ) as a proxy variable for digital finance. This decision is based on two factors: firstly, the CHFS database typically requests information about the previous year of the sampled households (e.g. their income and expenses from last year); secondly, the survey is usually conducted in the middle of the year or during the summer. Therefore, we believe that adjusting the *DFI* with a one-year lag is appropriate. If the previous Model (1) yields an inverted U-shaped relationship, then testing Hypothesis 2 is equivalent to examining the significance of the coefficient  $\beta_4$ . Generally, if  $\beta_4$  is positive, the

moderating effect of digital finance will flatten the inverted U-shaped curve; if  $\beta_4$  is negative, the moderating effect will make the curve steeper. Therefore,  $\beta_4$  is the primary coefficient of interest. However, this does not imply that  $\beta_1$ ,  $\beta_2$  and  $\beta_3$  are not economically significant. To better visualize the marginal impact of e-commerce participation on farmers' household income, Model (2) can be derived.

$$\frac{\partial E(Y|X)}{\partial Employ} = \beta_1 + 2\beta_2 Employ + \beta_3 DFI + 2\beta_4 Employ \times DFI \quad (3)$$

The marginal impact now relies on the values of *Employ*, the moderating term *DFI* and the four coefficients. Therefore, to accurately estimate the marginal effect, we can obtain the result using Equation (3) with the given values of the moderating variables and estimated coefficients. Furthermore, the partial derivative of Equation (3) concerning *DFI* can be calculated as follows:

$$\frac{\partial^2 E(Y|X)}{\partial Employ \partial DFI} = \beta_3 + 2\beta_4 Employ \quad (4)$$

When *Employ* strictly exceeds zero, the direction of Equation (4) depends on the coefficients  $\beta_3$  and  $\beta_4$ . Specifically, if  $\beta_3 + 2\beta_4 Employ$  is positive, the marginal impact of e-commerce will increase with an increase in the moderating variable *DFI*. This implies that digital finance can alleviate the diminishing marginal impact trend (inverted U-shaped) observed in Model (1). This finding is crucial as it confirms the existence of a synergistic relationship between digital finance and e-commerce participation. In the subsequent empirical analysis, some clear graphs will be given to illustrate the relationship among the three key variables ( $Employ_{ipt}$ ,  $DFI_{pt-1}$ ,  $Y_{ipt}$ ).

**3.3.3 Solving the endogeneity problem.** We argue that e-commerce participation may be endogenous because there may be unobservable omitted variables that affect both e-commerce participation and farmers' income (e.g. the digital literacy of individuals and their ability to use digital technology to enhance their economic well-being, etc.). In the identification of causality, we employed a panel fixed effects model for estimation and controlled of as many observable variables as possible, which can help us to mitigate endogeneity problems due to omitted variables. But that's not enough. Previous studies have mostly alleviated the endogeneity problem by finding instrumental variables. We tried to use the traditional method of analysis, i.e. adding the individual level to the macro level to obtain instrumental variables. However, the outcomes were unfavorable as the instrumental variables did not pass the multiple tests. Combining the above factors, we used a heteroscedasticity-based identification method following Lewbel (2012) approach. For more details on this approach, please see the literature by Lewbel (2012) and Baum and Lewbel (2019).

## 4. Empirical results and analysis

### 4.1 E-commerce participation and household income

Table 2 presents the results of the inverted U-shaped relationship test between e-commerce participation and farmers' household income in Model (1). Columns (1)–(3) examine only a single positive linear effect of e-commerce, which is commonly found in the literature. We provide results while controlling for province-fixed effects, two-way fixed effects and the addition of control variables. The results revealed that the coefficient of *Employ* was significantly positive, indicating a significant correlation between e-commerce participation and farmers' household income. Given the quadratic term of *Employ* in columns (4)–(6), the quadratic coefficient is statistically significant and negative. Additionally, the statistical

Table 2.  
The effect of  
e-commerce on the  
logarithm of per capita  
household income:  
fixed-effects model

| Variables                 | (1)                 | (2)                 | (3)                    | (4)                                             | (5)                                             | (6)                                                                                                                                                                                                                                                                                                                                                                                          |
|---------------------------|---------------------|---------------------|------------------------|-------------------------------------------------|-------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Employ</i>             | 0.0429*<br>(0.0200) | 0.0402*<br>(0.0221) | 0.0398*<br>(0.0160)    | 0.1725***<br>(0.0454)<br>-0.0223***<br>(0.0006) | 0.1621***<br>(0.0434)<br>-0.0002***<br>(0.0006) | 0.1119***<br>(0.0406)<br>-0.0016***<br>(0.0006)<br>0.0072<br>(0.0123)<br>-0.0068<br>(0.0116)<br>0.0155<br>(0.0667)<br>0.0506<br>(0.0935)<br>0.3676***<br>(0.0802)<br>0.3009***<br>(0.0476)<br>-0.0324**<br>(0.0140)<br>-1.2011***<br>(0.1181)<br>-0.3585***<br>(0.0908)<br>-0.1049<br>(0.5324)<br>-8.6505***<br>(2.4822)<br>-0.1147<br>(0.1324)<br>0.0088<br>(0.0066)<br>-1.4928<br>(1.3332) |
| <i>Employ<sup>2</sup></i> |                     |                     |                        |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Age</i>                |                     |                     | 0.0069<br>(0.0122)     |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Age<sup>2</sup></i>    |                     |                     | -0.0077<br>(0.0115)    |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Gender</i>             |                     |                     | 0.0128<br>(0.0663)     |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Married</i>            |                     |                     | 0.0482<br>(0.0632)     |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Health</i>             |                     |                     | 0.2677**<br>(0.0900)   |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Edu</i>                |                     |                     | 0.2044**<br>(0.0476)   |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Family size</i>        |                     |                     | -0.0327*<br>(0.0140)   |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Child</i>              |                     |                     | -1.2097***<br>(0.1181) |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Clap</i>               |                     |                     | -0.3600**<br>(0.0908)  |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Pro_jobgdp</i>         |                     |                     | -0.1120<br>(0.5319)    |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Pro_urban</i>          |                     |                     | -8.6758***<br>(2.4758) |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Pro_jobless</i>        |                     |                     | -0.1218<br>(0.1322)    |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Pro_phone</i>          |                     |                     | 0.0087<br>(0.0066)     |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| <i>Pro_consum</i>         |                     |                     | -1.6289<br>(1.3333)    |                                                 |                                                 |                                                                                                                                                                                                                                                                                                                                                                                              |
| Province FE               | Yes                 | Yes                 | Yes                    | Yes                                             | Yes                                             | Yes                                                                                                                                                                                                                                                                                                                                                                                          |
| Time FE                   | No                  | Yes                 | Yes                    | No                                              | Yes                                             | Yes                                                                                                                                                                                                                                                                                                                                                                                          |
| <i>N</i>                  | 8043                | 8043                | 8043                   | 8043                                            | 8043                                            | 8043                                                                                                                                                                                                                                                                                                                                                                                         |
| <i>R<sup>2</sup>_adj</i>  | 0.0273              | 0.0348              | 0.0576                 | 0.0286                                          | 0.0360                                          | 0.0632                                                                                                                                                                                                                                                                                                                                                                                       |
| <i>AIC</i>                | 31.004              | 30.940              | 30.576                 | 30.994                                          | 30.981                                          | 30.572                                                                                                                                                                                                                                                                                                                                                                                       |
| <i>BIC</i>                | 31.018              | 30.954              | 30.788                 | 31.015                                          | 30.952                                          | 30.794                                                                                                                                                                                                                                                                                                                                                                                       |

Note(s): Standard errors in parentheses clustered to the city level. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source(s): Authors' own work

significance of the core explanatory variables in the three columns improves, indicating that the estimation in Column (6) more accurately reflects the relationship between *Employ* and farmers' household income. Testing for an inverted U-shaped relationship—including the squared terms of the explanatory variables in the model and testing the significance of the coefficients of the squared terms—is a common practice in the existing literature. However, Lind and Mehlum (2010) argued that this practice may incorrectly classify concave-to-origin monotonic relationships as inverted U-shaped ones. Thus, we referred to Lind and Mehlum (2010) and performed a *U*-test. The *t*-statistic value is 2.69, corresponding to a *p*-value of 0.0039. The slope interval contains negative values, meaning that the effect of e-commerce participation on farmers' income is indeed inverted and U-shaped (the null hypothesis is rejected at the 1% significance level). Based on the estimates in Column (6), we calculated the location of the turning point to *Employ* = 38.2097, which is much larger than the mean, but still some distance away from the maximum. This confirms the validity of Hypothesis 1; that is, e-commerce involvement has an enhanced marginal decreasing effect on farmers' household income.

#### 4.2 The moderating effect of digital finance

Table 3 reports the estimated results of Model (2) established based on Hypothesis 2, which suggests that digital inclusive finance can alleviate the diminishing marginal effect between e-commerce participation and farmers' incomes. The results are consistent with Shamim's (2007) finding of a positive association between ICT penetration and financial development. Columns (1) and (2) show the moderating effect of digital finance on the inverted U-shaped relationship with and without control variables, respectively. At this point, the key coefficient  $\beta_4$  is positive and significantly non-zero, implying that digital finance can "flatten out" the inverted U-shaped relationship between e-commerce participation and farmers' incomes. Then, by calculating the result of  $\beta_1\beta_4 - \beta_2\beta_3$  ( $>0$ ), we know that the turning point moves to the right.

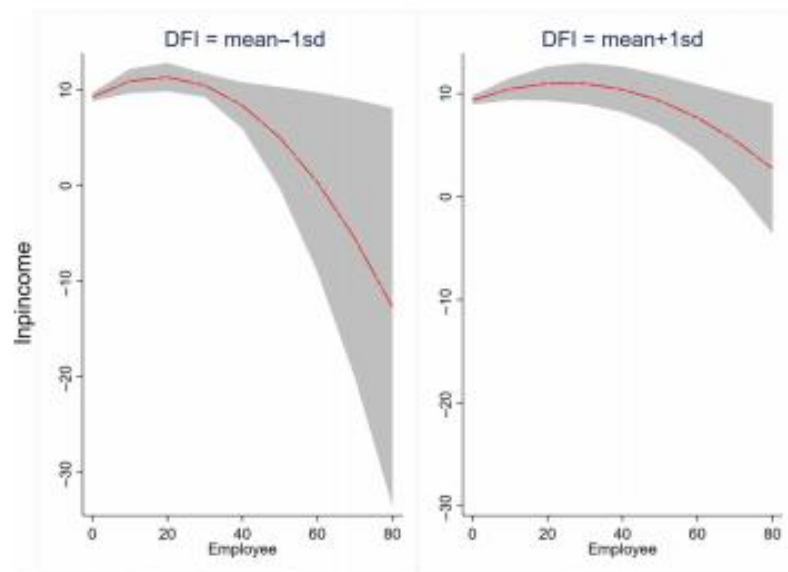
To illustrate the marginal effects of e-commerce on household income in the context of digital finance development, we present four graphs based on the estimation results of Model (2). Figures 1 and 2 demonstrate the inverted U-shaped relationship between *Employ* and income and depict the direction of the graph for different levels of digital finance. At low levels

| Variables                               | (1)                    | (2)                    | (3)                   | (4)                   |
|-----------------------------------------|------------------------|------------------------|-----------------------|-----------------------|
| <i>Employ</i>                           | 0.4907*<br>(0.2546)    | 0.4804*<br>(0.2531)    | 0.4176*<br>(0.2510)   | 0.3980*<br>(0.2386)   |
| <i>Employ</i> <sup>2</sup>              | -0.0188***<br>(0.0066) | -0.0174***<br>(0.0066) | -0.0156**<br>(0.0066) | -0.0127**<br>(0.0064) |
| <i>Employ</i> × <i>DFI</i>              | -0.0897<br>(0.0985)    | -0.0969<br>(0.0963)    | -0.0757<br>(0.0951)   | -0.0917<br>(0.0897)   |
| <i>Employ</i> <sup>2</sup> × <i>DFI</i> | 0.0049<br>(0.0022)     | 0.0046<br>(0.0022)     | 0.0040<br>(0.0022)    | 0.0035<br>(0.0021)    |
| <i>DFI</i>                              | 0.2975***<br>(0.0492)  | 0.2136***<br>(0.0427)  | 0.4469<br>(0.4501)    | 0.0764<br>(0.4258)    |
| Control variables                       | No                     | No                     | No                    | Yes                   |
| Province FE                             | No                     | Yes                    | Yes                   | Yes                   |
| Time FE                                 | No                     | No                     | Yes                   | Yes                   |
| <i>N</i>                                | 8,043                  | 8,043                  | 8,043                 | 8,043                 |
| <i>R</i> <sup>2</sup> <sub>adj</sub>    | 0.0112                 | 0.0324                 | 0.0361                | 0.0682                |

Note(s): Control variables include the set of variables in Table 2. Standard errors in parentheses clustered to the city level; \**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01

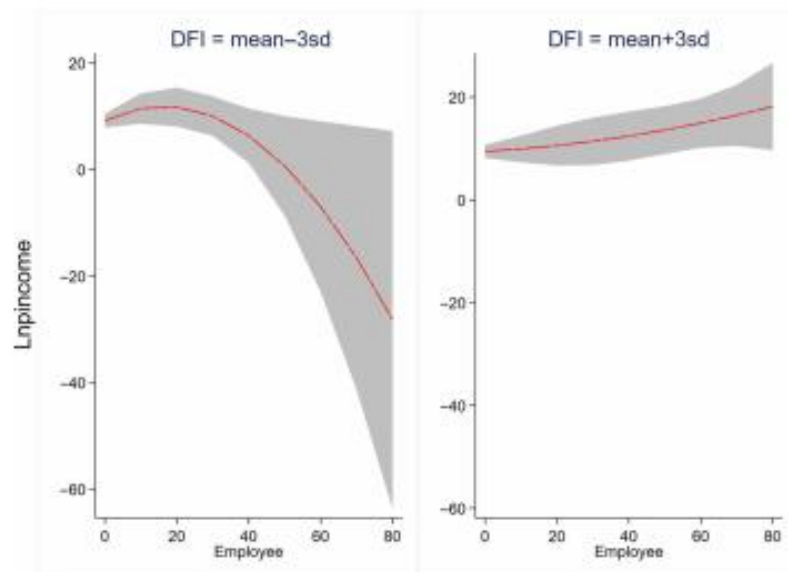
Source(s): Authors' own work

Table 3.  
Interaction effect of  
e-commerce and digital  
finance on household  
income



**Figure 1.**  
Interaction effect of  
*Employ* and *DFI* on  
household income  
(*DFI* = mean  $\pm$  1 sd)

Source(s): Authors' own work



**Figure 2.**  
Interaction effect of  
*Employ* and *DFI* on  
household income  
(*DFI* = mean  $\pm$  3 sd)

Source(s): Authors' own work

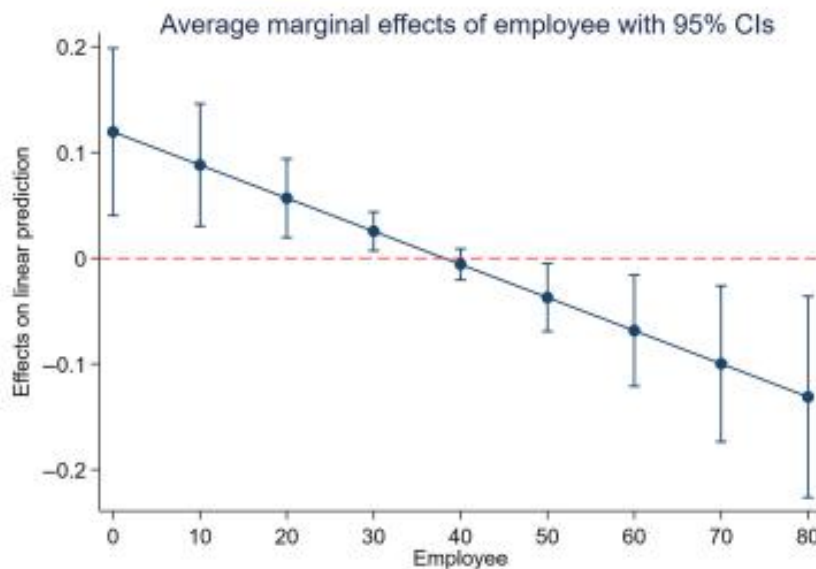
of digital finance, there is an inverted U-shaped curve between e-commerce participation and household income, supporting [Hypothesis 1](#). However, at higher levels of digital finance, the inverted U-shaped curve flattens. The Y-axis values also shift slightly upward at higher levels

of digital finance, indicating that the positive promotional effect of e-commerce participation is stronger. This reflects the synergistic effect of digital finance and e-commerce, in which the digital footprint and transaction information gathered by farmers during e-commerce participation can be transformed into credit scores, effectively reducing information asymmetry in the credit transaction process. Furthermore, microfinance expansion increases rural households' access to financial services and supports farmers' e-commerce participation.

In addition, we plotted the average marginal effects of *Employ* on household income. Figure 3 shows the marginal effects estimated from the baseline model using *Employ*<sup>2</sup>. The overall trend is downward and crosses the 0-value line, indicating that the marginal effects begin to diminish after crossing a certain value. This finding supports Hypothesis 1, which establishes an inverted U-shaped relationship. Figure 4 presents the estimated results after considering digital finance and its interaction terms. As digital finance increases, the marginal effect line flattens and tends to be parallel to and above the X-axis. This result illustrates that digital finance can turn a curve into a straight one. Improvements in financial markets can significantly enhance the revenue-raising effect of e-commerce participation.

#### 4.3 Consider the endogeneity problem

In the previous section, the identification strategy based on heteroskedasticity was briefly discussed. Referring to the study of Baum and Lewbel (2019), we chose  $Z = \{all\ of\ X\}$  (except the constant) to use for constructing the instruments  $(Z - \bar{Z})\epsilon_2$ . The Breusch-Pagan test was used to test whether the heteroskedasticity in first stage regression was satisfied, and the results showed that in each case, the  $p$ -value was 0.000, significantly rejecting the null hypothesis of homoskedasticity of the error term. One of the core assumptions for using the Lewbel (2012) estimator is met. Table 4 reports the results of models (1) and (2) using the two-stage estimation proposed by Lewbel (2012). The control variables remain consistent with those used in Tables 2 and 3. To verify the robustness of the different choices of  $Z$ , drawing on Mishra and Smyth (2015), we also report the estimated coefficients under different combinations in Appendix Table 1A.



Source(s): Authors' own work

Figure 3.  
Marginal effect with *Employ*<sup>2</sup>

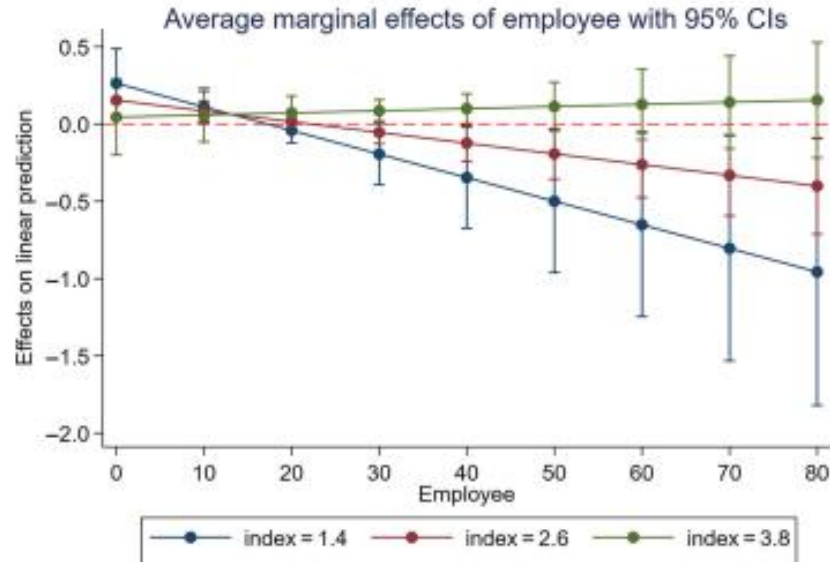


Figure 4.  
Marginal effect with  
 $Employ^2$  and  
interaction item

Source(s): Authors' own work

| Variables                             | (1)<br>Two-step GMM    | (2)<br>Two-step GMM    | (3)<br>Two-step GMM   | (4)<br>Two-step GMM   |
|---------------------------------------|------------------------|------------------------|-----------------------|-----------------------|
| <i>Employ</i>                         | 0.1104***<br>(0.0257)  | 0.0894***<br>(0.0231)  | 0.1689<br>(0.1183)    | 0.2081*<br>(0.1177)   |
| $Employ^2$                            | -0.0014***<br>(0.0003) | -0.0011***<br>(0.0003) | -0.0086**<br>(0.0031) | -0.0097**<br>(0.0032) |
| <i>Employ</i> × <i>DFI</i>            |                        |                        | 0.0186<br>(0.0470)    | 0.0042<br>(0.0455)    |
| $Employ^2$ × <i>DFI</i>               |                        |                        | 0.0017*<br>(0.0010)   | 0.0021**<br>(0.0010)  |
| <i>DFI</i>                            |                        |                        | 0.3867**<br>(0.1537)  | 0.1552<br>(0.4230)    |
| Control variables                     | Yes                    | Yes                    | Yes                   | Yes                   |
| Province FE                           | Yes                    | Yes                    | Yes                   | No                    |
| Time FE                               | No                     | Yes                    | No                    | Yes                   |
| <i>N</i>                              | 8,043                  | 8,043                  | 8,043                 | 8,043                 |
| $R^2_{adj}$                           | 0.064                  | 0.067                  | 0.063                 | 0.065                 |
| Kleibergen-Paap rk LM statistic       | 159.198<br>[0.000]     | 161.419<br>[0.000]     | -                     | -                     |
| Cragg-Donald Wald <i>F</i> -statistic | 670.353                | 693.586                | 6,464.283             | 2778.733              |
| Hansen <i>J</i> -statistic            | 81.382<br>[0.4985]     | 80.894<br>[0.6354]     | 181.934<br>[0.2188]   | 191.335<br>[0.2033]   |

Note(s): Control variables are consistent with Table 2; Robust standard errors in ( ); *p*-values in [ ]. Columns (1)–(4) are estimated based on the two-step GMM method. \**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01; *Z* = {*All of X*}, which contain province dummies and time dummies for the corresponding columns; The exogenous variable *DFI* is also included in *Z* for columns (3) and (4)

Source(s): Authors' own work

Table 4.  
Estimation results of  
IV method by  
Lewbel (2012)

The core coefficient estimates associated with the inverted U-shaped relationship and the moderating effect of digital finance remain robust. The test results indicate that the instrumental variables (IVs) based on heteroskedasticity work well, demonstrating strong capability in explaining the variation in e-commerce participation or digital finance. The Cragg-Donald Wald F statistic in all four columns is relatively high, and the  $p$ -values of the Hansen  $J$ -statistics are all greater than 0.1. Therefore, the null hypothesis that the Lewbel instrumental variable set satisfies exogeneity cannot be rejected. Finally, the Kleibergen-Paap RK LM statistic indicated that the instrumental variables pass the weak identification test. The key coefficient estimates of Table 4 using the two-step GMM are very similar to the OLS estimates both in value and statistical significance, and this evidence suggests that the baseline regression findings are robust. In particular, the coefficient of the squared interaction term is positive and significant at the 10% level, providing strong evidence of complementarity between e-commerce participation and digital finance.

#### 4.4 Further analysis

**4.4.1 Analysis of the moderating effect of digital finance sub-indicators.** To better understand the regulatory function of digital finance, we examined the influence of three sub-indexes of digital finance on the inverted U-shaped curve. The results show that coefficients of the squared interaction term  $\beta_4$  is all positive, but significant only when the interaction term is the degree of digitization. The digitization of finance relies on the empowerment of digital technology, such as big data and cloud computing. This enables the online processing of financial services, improves service efficiency and enhances user monitoring and credit systems. Consequently, digital finance facilitates financing and lending for e-commerce enterprises. The breadth of coverage does not exhibit a significant moderating effect, suggesting that digital finance has transitioned from regional promotion to deep penetration. However, rural residents exhibit limited acceptance of money funds, insurance, Internet investment and wealth management compared to urban areas. Please see Table 2A in the Appendix for results.

**4.4.2 Heterogeneity effect of household characteristics.** To further analyze the inverted U-shaped relationship between e-commerce participation and income, we conducted sub-sample regressions based on the gender of the household head and household income status. The results show that the positive moderating effect of digital finance is only significant in the sample where the household head is male. Rural women are more likely to face credit constraints compared to men with equivalent socioeconomic conditions (Fletschner, 2009; Diagne *et al.*, 2000). Such a gap may contribute to gender disparities in mathematical technology and potentially marginalize women in the digital technology sector (Vitores and Gil-Juárez, 2015). Similar patterns are observed in the sub-sample regression based on income. The moderating effect of digital finance is significant only among the non-poor sample. Limited financial literacy among low-income farmers may hinder their access to inclusive digital finance services. Please see Table 3A in the Appendix for results.

**4.4.3 Heterogeneity effect at the regional level.** The results show that the positive moderating effect of the inverted U-shaped curve is only observed in the sample from the eastern region. The eastern coastal region has a natural advantage in e-commerce and digital finance development due to its proximity to maritime ports and high level of economic development. Rural residents in the East demonstrate greater utilization of traditional finance and the internet compared to other regions. However, the regression results differ in the central region, where a U-shaped relationship emerges between e-commerce participation and farmers' household income. This finding aligns with Evans' (2018) study on the non-linear association between Internet use and agricultural development. The central region's less favorable e-commerce infrastructure and market environment in its early stages may contribute to this relationship. Moreover, being primarily a grain-producing area, many rural regions in the central area face economic challenges, low business investment and inadequate infrastructure, which require higher costs for sustaining

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e-commerce activities. As the market environment improves and e-commerce penetration increases, the revenue-raising potential of e-commerce gradually becomes evident. Please see Table 4A in the Appendix for results.

### 4.5 Mechanism analysis

Access to capital is crucial for e-commerce players to thrive. They need continuous investment to improve their online products' quality and productivity, enhance customer service and maintain a good reputation, ensuring a steady flow of consumer visits. The results in Table 5 show that digital finance can increase credit availability for rural households. With improved access to capital, e-commerce participants can invest in online product production and store management, ensuring the stability of their revenues. Then, we analyzed the impact of digital finance on the risk attitudes and innovation activities of e-commerce participants. Table 5 presents the results regarding the effect of digital finance on innovation investment and risk attitude in e-commerce projects. The coefficients of the squared interaction term  $Employ^2 \times DFI$  are both statistically significant and positive. Furthermore, increased investment in innovation and improved risk attitudes have a positive impact on household income.

## 5. Conclusion

Achieving sustained growth in farmers' household income is crucial for consolidating the results of poverty eradication strategies and moving toward rural revitalization and prosperity. The rapid growth of e-commerce and digital finance in China's rural areas has profoundly altered the production and business behavior of farmers and their social well-being. Currently, there is no quantitative economic research that explores the moderating effect of digital finance on the nonlinear income effects of rural households participating in e-commerce.

| Variables                               | (1)<br><i>Lndebt</i>  | (2)<br><i>Lnpincome</i> | (3)<br><i>Lninvest</i> | (4)<br><i>Lnpincome</i> | (5)<br><i>Risk</i>    | (6)<br><i>Lnpincome</i> |
|-----------------------------------------|-----------------------|-------------------------|------------------------|-------------------------|-----------------------|-------------------------|
| <i>Employ</i>                           | 1.2534<br>(0.8171)    | 0.2889<br>(0.2527)      | 2.1967***<br>(0.6907)  | 0.2852<br>(0.2510)      | 0.5469<br>(0.4786)    | -0.0012<br>(0.7987)     |
| <i>Employ</i> <sup>2</sup>              | -0.0506**<br>(0.0219) | -0.0087<br>(0.0069)     | -0.0704***<br>(0.0192) | -0.0090<br>(0.0068)     | -0.0399**<br>(0.0192) | -0.0255<br>(0.0352)     |
| <i>Employ</i> × <i>DFI</i>              | -0.3373<br>(0.3147)   | -0.0657<br>(0.0929)     | -0.6342***<br>(0.2298) | -0.0603<br>(0.0919)     | -0.1251<br>(0.1530)   | 0.0395<br>(0.2419)      |
| <i>Employ</i> <sup>2</sup> × <i>DFI</i> | 0.0152**<br>(0.0072)  | 0.0023<br>(0.0022)      | 0.0208***<br>(0.0060)  | 0.0024<br>(0.0022)      | 0.0115**<br>(0.0057)  | 0.0072<br>(0.0104)      |
| <i>DFI</i>                              | 3.3608**<br>(1.6532)  | 0.5025<br>(0.4722)      | -0.0846<br>(0.4310)    | 0.1190<br>(0.4272)      | 1.0701*<br>(0.6244)   | 1.5555*<br>(0.8558)     |
| <i>Lndebt</i>                           |                       | 0.0077<br>(0.0041)      |                        |                         |                       |                         |
| <i>Lninvest</i>                         |                       |                         |                        | 0.0428***<br>(0.0097)   |                       |                         |
| <i>Risk</i>                             |                       |                         |                        |                         |                       | 0.1038***<br>(0.0293)   |
| Control variables                       | Yes                   | Yes                     | Yes                    | Yes                     | Yes                   | Yes                     |
| Province FE                             | Yes                   | Yes                     | Yes                    | Yes                     | Yes                   | Yes                     |
| Time FE                                 | Yes                   | Yes                     | Yes                    | Yes                     | Yes                   | Yes                     |
| <i>N</i>                                | 6,282                 | 6,282                   | 7,967                  | 7,967                   | 2,607                 | 2,607                   |
| <i>R</i> <sup>2</sup> <sub>adj</sub>    | 0.2230                | 0.0757                  | 0.0371                 | 0.0688                  | 0.1230                | 0.0676                  |

Note(s): Control variables consistent with Table 2; Standard errors in parentheses clustered to city level;

\**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01

Source(s): Authors' own work

Table 5.  
Mechanism test

Using a combination of macro and micro data, this study provides insights into the income effects of e-commerce participation and the inverted U-shaped moderating effect of digital finance. The results show a significant inverted U-shaped relationship between farmers' e-commerce participation and their incomes, which makes it difficult for farmers to sustain their income growth as their participation deepens and market competition intensifies, illustrating the need for the central government to implement relevant policies to support the transformation and upgrading of rural e-commerce. Second, digital finance has a significant moderating effect on the inverted U-shaped marginal effect curve. These findings remain reliable after considering potential inherent problems. We also found that this moderating effect varied across the classification indicators of digital inclusion. Finally, we found that the alleviation of credit constraints, an increase in innovation investment and a decrease in risk aversion are important paths for e-commerce and digital finance to jointly promote the sustainable growth of farmers' incomes.

Finally, we propose that the government support the transformation and upgrading of rural e-commerce and we encourage e-commerce entities to innovate products and services to avoid falling into the quagmire of price wars. In addition, the depth of usage of digital finance has a limited role, and the penetration of Internet investment and finance, insurance and other businesses in rural areas is insufficient. Hence, we suggest that farmers should receive ongoing training in digital skills and financial knowledge to gradually improve their risk attitude and guarantee the income-generating effect of e-commerce.

#### Notes

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2. National Bureau of Statistics, China. Resident income and consumer spending in 2022. [http://www.stats.gov.cn/tjsj/zxfb/202301/t20230117\\_1892088.html](http://www.stats.gov.cn/tjsj/zxfb/202301/t20230117_1892088.html)
3. Xinhua Daily. Xu Guanying, Wang Xiaoxia. "Visiting 'Disappearing' Taobao Villages: How to Address the Challenges of New Business Formats". <http://js.xhby.net/system/2018/07/14/030855079.shtml>
4. A "Taobao Village" refers to a village where the number of active online shops exceeds 10% of the total number of households (or has at least 100 active online shops), and the annual e-commerce transaction volume reaches over 10 million yuan (approximately 1 million US dollars) or more.

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(The Appendix follows overleaf)

| Variables                                 | E-commerce participation   |                      |                               |
|-------------------------------------------|----------------------------|----------------------|-------------------------------|
|                                           | (1)<br>Breadth of coverage | (2)<br>Depth of use  | (3)<br>Degree of digitization |
| <i>Employ</i>                             | 0.3217<br>(0.2575)         | 0.3366*<br>(0.1925)  | 0.6136**<br>(0.2367)          |
| <i>Employ</i> <sup>2</sup>                | -0.0121<br>(0.0069)        | -0.0102*<br>(0.0054) | -0.0177**<br>(0.0062)         |
| <i>Employ</i> × <i>Cover</i>              | -0.0645<br>(0.1031)        |                      |                               |
| <i>Employ</i> <sup>2</sup> × <i>Cover</i> | 0.0034<br>(0.0023)         |                      |                               |
| <i>Cover</i>                              | 1.3245*<br>(0.7585)        |                      |                               |
| <i>Employ</i> × <i>Usage</i>              |                            | -0.0718<br>(0.0733)  |                               |
| <i>Employ</i> <sup>2</sup> × <i>Usage</i> |                            | 0.0027<br>(0.0018)   |                               |
| <i>Usage</i>                              |                            | -0.1764<br>(0.2529)  |                               |
| <i>Employ</i> × <i>Digit</i>              |                            |                      | -0.1384*<br>(0.0713)          |
| <i>Employ</i> <sup>2</sup> × <i>Digit</i> |                            |                      | 0.0042**<br>(0.0016)          |
| <i>Digit</i>                              |                            |                      | 0.0096<br>(0.1305)            |
| Control variables                         | Yes                        | Yes                  | Yes                           |
| Province FE                               | Yes                        | Yes                  | Yes                           |
| Time FE                                   | Yes                        | Yes                  | Yes                           |
| <i>N</i>                                  | 8,043                      | 8,043                | 8,043                         |
| <i>R</i> <sup>2</sup> <sub>adj</sub>      | 0.0684                     | 0.0681               | 0.0682                        |

Note(s): Control variables consistent with Table 2; Standard errors in parentheses clustered to city level;  
 \**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01  
 Source(s): Authors' own work

**Table A2.**  
Interaction between  
e-commerce and digital  
finance sub-indicators  
on the household  
income

| Variables                               | (1)<br>Non-poor       | (2)<br>Poor           | (3)<br>Male          | (4)<br>Female       |
|-----------------------------------------|-----------------------|-----------------------|----------------------|---------------------|
| <i>Employ</i>                           | 0.4159*<br>(0.2483)   | -5.3756**<br>(2.6678) | 0.3117<br>(0.2339)   | 0.9132*<br>(0.4939) |
| <i>Employ</i> <sup>2</sup>              | -0.0132**<br>(0.0067) | 2.6799***<br>(0.9018) | -0.0345*<br>(0.0193) | 0.0468<br>(0.0309)  |
| <i>Employ</i> × <i>DFT</i>              | -0.0968<br>(0.0925)   | 1.8992<br>(1.1467)    | -0.0563<br>(0.0796)  | -0.1416<br>(0.1896) |
| <i>Employ</i> <sup>2</sup> × <i>DFT</i> | 0.0036<br>(0.0021)    | -1.0221**<br>(0.3956) | 0.0099<br>(0.0055)   | -0.0316<br>(0.0164) |
| <i>DFT</i>                              | -0.0369<br>(0.4401)   | 2.6128<br>(1.8355)    | 0.0011<br>(0.4572)   | 0.1968<br>(1.3623)  |
| Control variables                       | Yes                   | Yes                   | Yes                  | Yes                 |
| Province FE                             | Yes                   | Yes                   | Yes                  | Yes                 |
| Time FE                                 | Yes                   | Yes                   | Yes                  | Yes                 |
| <i>N</i>                                | 7,684                 | 359                   | 6,885                | 1,158               |
| <i>R</i> <sup>2</sup> <sub>adj</sub>    | 0.0652                | 0.0948                | 0.0655               | 0.0856              |

Note(s): Control variables consistent with Table 2; Robust standard errors in parentheses; \**p* < 0.1,  
 \*\**p* < 0.05, \*\*\**p* < 0.01  
 Source(s): Authors' own work

**Table A3.**  
Heterogeneity analysis  
I: micro perspective

## CAER

| Variables                               | (1)<br>East            | (2)<br>Central        | (3)<br>West         | (4)<br>Northeast    |
|-----------------------------------------|------------------------|-----------------------|---------------------|---------------------|
| <i>Employ</i>                           | 0.6510**<br>(0.2965)   | -4.8563**<br>(1.9552) | 0.2388<br>(2.2676)  | 6.5580<br>(5.2290)  |
| <i>Employ</i> <sup>2</sup>              | -0.0209***<br>(0.0072) | 0.6367**<br>(0.2486)  | 1.0408<br>(1.0835)  | -7.6708<br>(6.1425) |
| <i>Employ</i> × <i>DFI</i>              | -0.1513<br>(0.1150)    | 1.7433*<br>(0.6896)   | 0.1423<br>(1.0581)  | -2.3329<br>(2.1386) |
| <i>Employ</i> <sup>2</sup> × <i>DFI</i> | 0.0057**<br>(0.0024)   | -0.2240**<br>(0.0864) | -0.5251<br>(0.5062) | 3.0635<br>(2.4316)  |
| <i>DFI</i>                              | 0.4595<br>(0.9587)     | -0.7255<br>(2.1701)   | 2.1710<br>(1.8536)  | 4.4048<br>(4.9721)  |
| Control variables                       | Yes                    | Yes                   | Yes                 | Yes                 |
| Province FE                             | Yes                    | Yes                   | Yes                 | Yes                 |
| Time FE                                 | Yes                    | Yes                   | Yes                 | Yes                 |
| <i>N</i>                                | 3,717                  | 1,764                 | 2,018               | 544                 |
| <i>R</i> <sup>2</sup> <sub>adj</sub>    | 0.0757                 | 0.0587                | 0.0457              | 0.0250              |

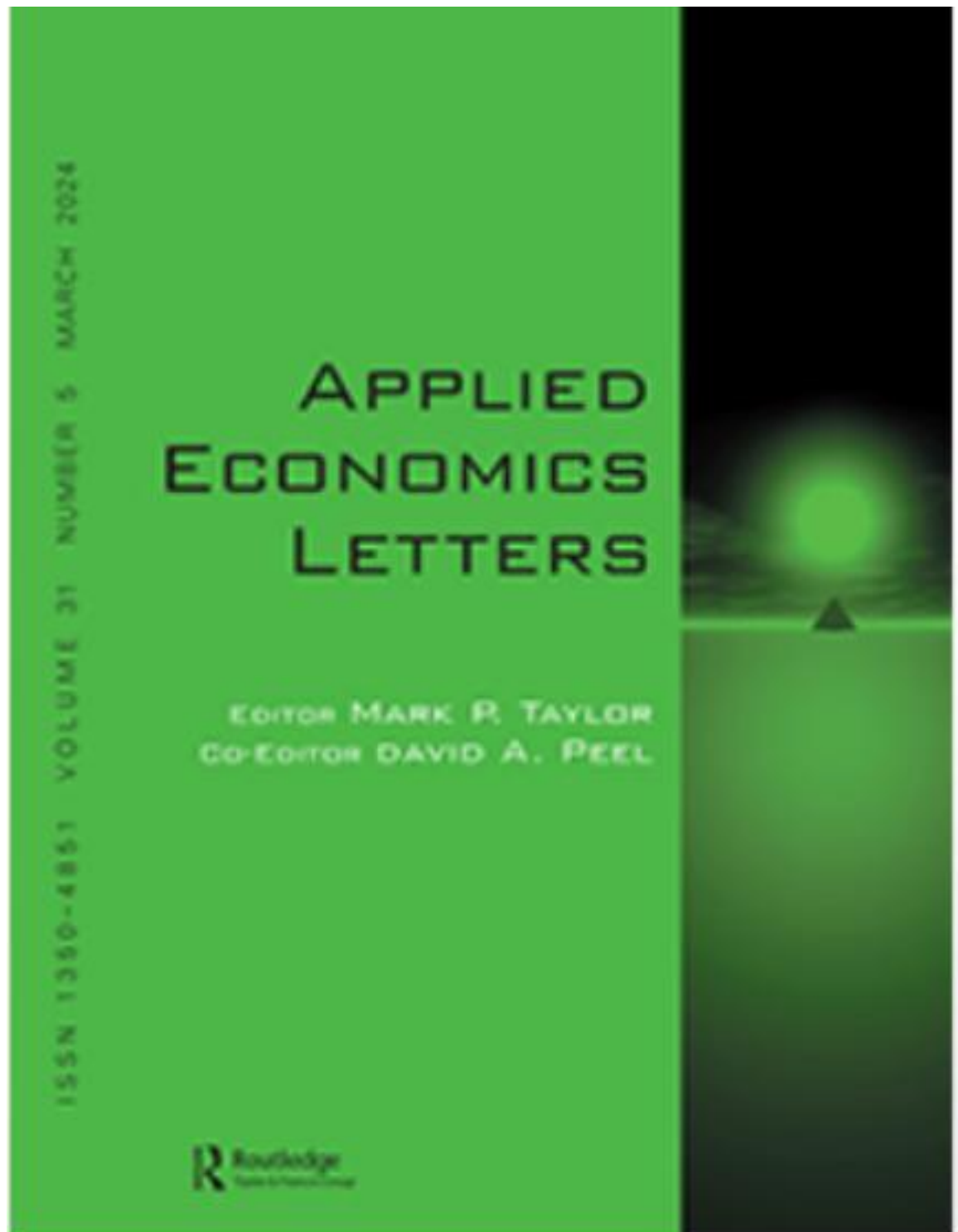
Table A4. Note(s): Control variables consistent with Table 2; Standard errors in parentheses clustered to city level; Heterogeneity analysis \**p* < 0.1, \*\**p* < 0.05, \*\*\**p* < 0.01  
II: macro perspective Source(s): Authors' own work

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### 3. 2. The impact of e-commerce activities on rural household leverage



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ARTICLE



## The impact of e-commerce activities on rural household leverage

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### ABSTRACT

This article provides new evidence on the connection between e-commerce and rural household leverage in China. We find that e-commerce activities increase the leverage ratio of Chinese rural households significantly, especially in the west region, households headed by men, and households that have not experienced borrowing denials. The results are still robust when using an instrumental variable approach to solve endogenous problems. The findings suggest that participation in e-commerce may relieve the constraint of formal credit, which will boost the household leverage.

### KEYWORDS

E-commerce; rural families; household leverage; credit constraint

### JEL CLASSIFICATION

Q12; O18

### 1. Introduction

Rural areas are the stabilizers of China's economy. The debt situation of rural households is related to the long-term development of the rural economy. According to the OECD database, the asset-liability ratio of residents in the world's major economies, commonly used as a measure of household leverage, is mostly between 10–20%. The ratio of Chinese residents increased from 4.42% in 2000 to 10.84% in 2019 (Li and Zhang 2020), which is on the low side of international comparison. The rural credit market has been facing severe credit constraints due to high transaction costs and the lack of particularity of traditional collateral (Stiglitz and Weiss 1981; Zhao and Peter 2014; Li, Lin, and Gan 2016), so there is still room for more leverage to improve the property income of farmers. Credit access has a positive impact on rural households' income growth, poverty reduction, and improvement of economic vulnerability (Peng, Ren, and Li 2021).

Meanwhile, information communication technology (ICT) has accelerated its penetration into rural areas. ICT helps to reduce the operating cost of the capital supplier, the search cost and the conversion cost of the capital demand side, and thus improve the credit availability and lending scale of borrowers (Shamim 2007). As a representative

application of ICT in the countryside, e-commerce makes it possible for digital dividends to benefit rural areas better (Leroux, Wortman, and Mathias 2001). The introduction of rural e-commerce has increased the sales path of farmers' agricultural products, promoted the growth of e-commerce sales, and changed the unfavourable situation that farmers used to be price recipients (Goldfarb and Tucker 2019). Furthermore, Digital information such as sales data and payment records left by farmers on the e-commerce platform can be converted into credit scores through financial technology, thus reducing information asymmetry and transaction costs in credit transactions (Dong, Ren, and Zhang 2019). In addition, the development of rural e-commerce is typically aggregative and can generate greater supply-side economies of scale, thus enabling farmers to better access to digital credit support (Dunt and Harper 2002; Zhang et al. 2018). E-commerce participation provides a new opportunity for rural families to obtain digital credit.

Previous studies on household financial decision-making have focused more on the unilateral inspection of assets or liabilities. This paper is more in line with the actual situation by a joint investigation of them to analyse the impact of e-commerce participation on the leverage ratio of rural households and explore the internal mechanism.

## II. Model and data

To analyse the impact of e-commerce on household leverage, we choose the fixed effect model and use clustered robust standard errors to eliminate the influence of heteroscedasticity:

$$\text{leverage}_{ist} = \beta_0 + \beta_1 \times \text{ECA}_{ist} + \beta_2 \times X_{ist} + \gamma_i + \varepsilon_{ist} \quad (1)$$

where  $\text{leverage}_{ist}$  is the household leverage of householders  $i$  in provinces in year  $t$ , which is equal to household debt divided by household assets.<sup>1</sup> The main explanatory variable  $\text{ECA}_{ist}$  is the electronic commercial activity of householders, which includes the use of online banking, online payment, online shopping and other online transaction activities.  $X_{ist}$  is a series of control variables including individual characteristic variables such as age, the square of age, education, marital status, etc. It also contains family and provincial characteristic variables.  $\gamma_i$  represents individual fixed effects and  $\varepsilon_{ist}$  is a disturbance term.

Data are mainly derived from China Family Panel Studies (CFPS). We use three waves of data in 2014, 2016, and 2018. The final unbalanced panel data are obtained for 3713 rural households. Table 1 presents the descriptive statistics.

## III. Results and discussion

We are concerned that unobserved factors such as financial literacy could affect the probability of participating in e-commerce and household leverage, in which case OLS estimates would be biased. So we turn to the IV method. The choice of instrumental variables draws on Zhou, Cui, and Zhang's (2020) study, where we selected the average spare time spent online at the village level and the number of cell phone subscribers at the provincial level as instrumental variables. The average spare time spent online in the village reflects the online climate and online interaction between acquaintances. This will help the rapid transmission of commercial information and can positively influence farmers' e-commerce participation. The number of cell phone subscribers in the province responds to the size of online consumers, which helps the implementation of commercial activities. In addition, both instrumental variables are macro-level factors, and it is difficult for individual behaviour to influence macro-level factors, so exogeneity is satisfied.

Table 2 shows the main result. Column (1) shows the OLS estimation results of Eq. (1). The Durbin-Wu-Hausman test was used to test for the presence of endogeneity in ECA. The results significantly rejected the original hypothesis. So we then report the 2SLS estimation results. Column (2)-(3) show that the coefficient  $\beta_1$  is positive and

Table 1. Summary statistics.

| Variable     | Description                                                                     | Obs. | Mean   | St. Dev. | Min   | Max    |
|--------------|---------------------------------------------------------------------------------|------|--------|----------|-------|--------|
| Lever        | Household leverage(HH debt/HH asset)                                            | 8772 | 0.156  | 0.405    | 0     | 4.106  |
| ECA_dummy    | Dummy of e-commerce participation                                               | 8772 | 0.123  | 0.329    | 0     | 1      |
| ECA_freq     | Frequency of e-commerce participation                                           | 8772 | 0.372  | 1.129    | 0     | 6      |
| Age          | Age of householder                                                              | 8772 | 45.715 | 8.954    | 18    | 60     |
| Edu          | Years of householder's education                                                | 8772 | 6.539  | 4.128    | 0     | 19     |
| Married      | Marital status of householder (1=Being married)                                 | 8772 | 0.900  | 0.299    | 0     | 1      |
| Health       | Self-evaluated health status(1=good)                                            | 8772 | 0.823  | 0.382    | 0     | 1      |
| Fsize        | Family size                                                                     | 8772 | 4.134  | 1.759    | 1     | 14     |
| Lnhpincome   | Per capita net income of family(logarithm)                                      | 8772 | 8.949  | 1.255    | 0     | 12.767 |
| Social       | Per capita social and gift expenses (logarithm)                                 | 8772 | 5.863  | 2.137    | 0     | 11.156 |
| Nchild       | Number of children under 16                                                     | 8772 | 0.806  | 0.963    | 0     | 6      |
| Nelder       | Number of children under 6                                                      | 8772 | 0.309  | 0.594    | 0     | 3      |
| House_own    | Residence ownership(1=yes)                                                      | 8772 | 0.910  | 0.286    | 0     | 1      |
| Pro_pincome  | Provincial per capita disposable income of rural residents (logarithm)          | 8772 | 1.137  | 0.356    | 0.628 | 3.037  |
| Pro_pconsume | Provincial per capita consumption of rural residents (logarithm)                | 8772 | 1.449  | 0.649    | 0.678 | 4.530  |
| Pro_pinvest  | Provincial per capita investment in fixed assets of rural residents (logarithm) | 8772 | 0.152  | 0.059    | 0.014 | 0.484  |
| Vill_avgtime | Average weekly spare time online at the village level                           | 8772 | 3.463  | 3.284    | 0     | 26.667 |
| Lnpuser      | Provincial cell phone subscribers (logarithm)                                   | 8772 | 8.485  | 0.569    | 7.209 | 9.731  |

<sup>1</sup>As this topic is related to the family financial situation, we regard the main financial respondent as the head of the household.

Table 2. E-commerce and rural household leverage.

|                                    | (1)                  | (2)                   | (3)                   | (4)                   | (5)                          | (6)                             | (7)                              | (8)                                |
|------------------------------------|----------------------|-----------------------|-----------------------|-----------------------|------------------------------|---------------------------------|----------------------------------|------------------------------------|
|                                    | OLS                  |                       |                       |                       | 2SLS                         |                                 |                                  |                                    |
|                                    | HH debt/<br>HH asset | HH debt/<br>HH asset  | HH debt/<br>HH asset  | HH debt/<br>HH income | HH bank<br>debt/<br>HH asset | HH nonbank<br>debt/<br>HH asset | HH time<br>deposits/<br>HH asset | HH demand<br>deposits/<br>HH asset |
| ECA_dummy                          | 0.033*<br>(0.019)    | 0.542*<br>(0.291)     |                       | 1.257*<br>(0.758)     | 0.377***<br>(0.137)          | 0.100<br>(0.233)                | 0.348<br>(0.265)                 | 0.145<br>(0.176)                   |
| ECA_freq                           |                      |                       | 0.146*<br>(0.086)     |                       |                              |                                 |                                  |                                    |
| Control variables                  | Y                    | Y                     | Y                     | Y                     | Y                            | Y                               | Y                                | Y                                  |
| Individual FE                      | Y                    | Y                     | Y                     | Y                     | Y                            | Y                               | Y                                | Y                                  |
| First-stage:<br>vill_avgtime       |                      | 0.003**<br>(0.001)    | 0.014***<br>(0.005)   | 0.003*<br>(0.002)     | 0.003**<br>(0.001)           | 0.003**<br>(0.001)              | 0.001<br>(0.002)                 | 0.002<br>(0.003)                   |
| lnuser                             |                      | 0.317***<br>(0.078)   | 1.045***<br>(0.305)   | 0.322***<br>(0.083)   | 0.317***<br>(0.078)          | 0.317***<br>(0.078)             | 0.390***<br>(0.129)              | 0.374***<br>(0.132)                |
| Control variables                  |                      | Y                     | Y                     | Y                     | Y                            | Y                               | Y                                | Y                                  |
| Individual FE                      |                      | Y                     | Y                     | Y                     | Y                            | Y                               | Y                                | Y                                  |
| Kleibergen-Paap rk LM<br>statistic |                      | 12.926***<br>(0.0016) | 12.520***<br>(0.0019) | 11.477***<br>(0.0032) | 12.926***<br>(0.0016)        | 12.926***<br>(0.0016)           | 7.769**<br>(0.0206)              | 6.939**<br>(0.0311)                |
| Cragg-Donald Wald F statistic      |                      | 16.312                | 17.305                | 14.892                | 16.312                       | 16.312                          | 6.470                            | 5.949                              |
| Hansen J statistic                 |                      | 0.799<br>(0.3715)     | 1.226<br>(0.2682)     | 0.236<br>(0.6273)     | 0.260<br>(0.6103)            | 0.398<br>(0.5282)               | 2.701<br>(0.1003)                | 0.683<br>(0.4085)                  |
| Observations                       | 8772                 | 8772                  | 8772                  | 8262                  | 8772                         | 8772                            | 3615                             | 3485                               |

Robust standard errors in parentheses are clustered at the individual level; \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . The bank debt here does not include housing loans.

statistically significant, with the household debt-to-asset ratio as the dependent variables. Column (4) replaces the dependent variable with the debt-to-income ratio of the household. They suggest that ECA will increase rural household leverage. Column (5)-(8) replace the dependent variables with the ratio of bank debt, non-bank debt, time deposits, and liquidity to household assets, respectively. The results show that ECA boosts household leverage mainly by increasing bank loans. E-commerce activities have increased farmers' access to formal credit.

To analyse the difference in the impacts of e-commerce, we have a sub-sample discussion based on considering endogenous. Table 3 shows that the coefficients are more significant in the western region, in rural households headed by

men, and in rural households without borrowing denials. The unpaired sample  $t$ -test shows that rural households in the west have significantly lower asset levels and income levels than rural households in the centre and east, but they are not very different in terms of debt levels. This makes the average debt leverage of western households higher than that of other regions. Farmers in the western region have higher credit needs, and participation in ECA can broaden their information channels and financing channels. In terms of gender differences, men are more popular in the credit market (Wahidi 2017; Bahta, Strydom, and Donkor 2017). They have a higher tolerance for risk, greater self-confidence, and more positive attitudes in the face of uncertainty (Croson and Gneezy 2009). Therefore, male household heads

Table 3. Heterogeneity analysis.

|                   | (1)               | (2)              | (3)               | (4)              | (5)              | (6)              | (7)                |
|-------------------|-------------------|------------------|-------------------|------------------|------------------|------------------|--------------------|
|                   | 2SLS              |                  |                   |                  |                  |                  |                    |
|                   | East              | Center           | West              | Female           | Male             | Loan refused     | No loan refused    |
| ECA_dummy         | -0.647<br>(0.726) | 0.394<br>(0.891) | 0.426*<br>(0.221) | 0.560<br>(1.139) | 0.439<br>(0.275) | 0.478<br>(1.642) | 1.154**<br>(0.542) |
| Control variables | Y                 | Y                | Y                 | Y                | Y                | Y                | Y                  |
| Individual FE     | Y                 | Y                | Y                 | Y                | Y                | Y                | Y                  |
| Observations      | 2930              | 2439             | 3375              | 4124             | 4647             | 1292             | 3126               |

Robust standard errors in parentheses are clustered at the individual level; \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

will be more receptive to e-commerce technology and more involved in activities. Therefore, they are more inclined to broaden their credit channels and expand the scale of reproduction through e-commerce activities. In addition, farmers who have no experience of borrowing rejection tend to have a better credit record in the credit market, with more ample room for increased leverage.

#### IV. Conclusion

Using three waves of data of CFPS, we estimated the impact of e-commerce participation on the household leverage of Chinese rural families. This finding suggests that e-commerce may strengthen the leverage level, especially in less developed areas, in rural households headed by men, and in rural households without borrowing denials. E-commerce activities boost household leverage mainly by increasing formal institutional lending.

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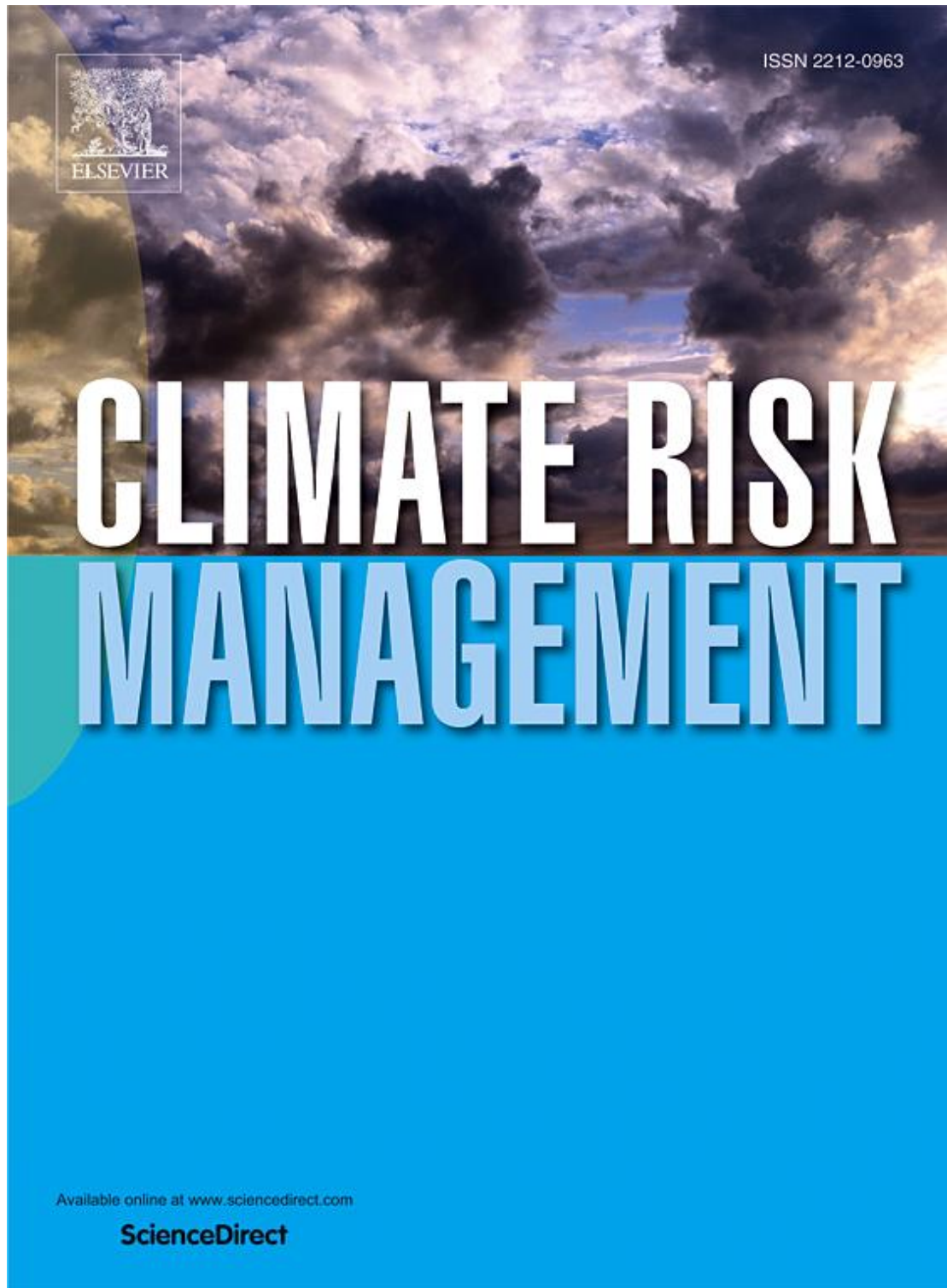
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### 3. 3. Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty




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## Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty

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## ABSTRACT

Livestock has a considerable role in the well-being of poor rural households in many developing countries. On the other hand, its productivity is adversely affected by climatic changes mainly due to the absence or non-adoption of effective and modern mitigation and adaptation strategies. The geographical locations and socio-economic conditions of developing countries make livestock herders, especially the smaller ones, more vulnerable while their capabilities to mitigate the adverse effects with limited resources will exacerbate the situation in the future. Most of the efforts to face climatic changes are directed at crop sector while only a few studies document such actions to safeguard livestock sector with similar focus notwithstanding the huge impact of these stimuli on this sub-sector of agriculture. This study uses propensity score matching (PSM) to assess the causal impact of climate change adaptation strategies on livestock losses and poverty by using the primary data set of 405 small livestock herders of Punjab, Pakistan. The PSM analysis points towards a massive potential for reducing these losses. The livestock losses and poverty index are shown to decline respectively by 30–48% and 4–22% for the farmers adopting a mix of mitigation strategies. Such outcome is believed to sustain environment and livestock herders' well-being. Results indicate that livestock herders easily adopt those strategies that have greater linkages with accessibility and resource availability. Study reveals the significance of improving infrastructure for speedy access to information, resources and uninterrupted flow of veterinary services. The vet personnel also need to be equipped with precise statistics of disease existence, impacts, dispersal, and costs for control by restructuring and advancing data collection efforts that would entail coherent policy formulation amidst evidence-based outcomes. The results do imply allocation of huge investment in the information delivery system; competitive institutional services and particular safeguarding of the resource-poor farmers to sustain livelihoods, food security and rural development.

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## 1. Introduction

Globally, livestock system supports more than one billion people (for food, nutrient security and income) (Rosegrant et al., 2009) by offering 1100 million jobs all over the world. Among these, little over 70% livestock herders belong to rural areas of developing countries (Herrero et al., 2012; Thornton et al., 2009). In many of these developing countries, a significant part of income comes from livestock (Thornton et al., 2009) and is considered as a prime asset for the majority of poor households within the most south Asian countries (Hurst, 2005). It is further noted that rural communities' reliance on livestock has increased manifold in the past three decades (Thornton et al., 2014). In Pakistan, livestock sector has multifarious benefits both for the national economy (by its more than 11% contribution in the country's GDP) and individual households in rural areas by being a source of investment with greater liquidity for risk minimization and a source of nutrient-rich diet (GOP, 2018; Thornton et al., 2015). Generally, landless and small livestock herders in the country generate a considerable part of their incomes from livestock (GOP, 2018) who are prone to multiple risks in the current era of changing climatic scenarios.

At present, livestock systems are facing enormous challenge to fulfil the global demand because of two contrasting factors: First, increasing demand due to population growth and urbanization (Intergovernmental Panel on Climate Change, 2014; Thornton and Gerber, 2010), and second, adverse climatic shocks disrupting livestock productivity – both in terms of quality and quantity (Thornton et al., 2015). According to the Global Climate Risk Index 2018, Pakistan is amongst the top ten most-affected countries due to climate change (David Eckstein et al., 2018; Faisal et al., 2021; Faisal et al., 2020). Extant literature shows that qualitative and quantitative shocks on livestock productivity resulting from climate change are mediated through poor quality fodders, forages and feed; and a higher incidence of livestock diseases (Bett et al., 2017; Rigolot et al., 2017; Seerapu et al., 2015). Multiple factors such as inadequate access to veterinary services, poor knowledge and suboptimal living conditions etc. do contribute to the occurrence, spread, poor control, persistence and spillovers of livestock diseases leading to heavy livestock losses (Rahut and Ali, 2018; Banik et al., 2015; Bernabucci, 2019; de Lauwere et al., 2012; Kauppinen et al., 2012; Nardone et al., 2010; Senger et al., 2017; St-Pierre et al., 2003). In addition, flooding and intermittent droughts have also been the source of physical damage and considerable mortalities of animals who are less-resistant to such vagaries (Dublin and Ogutu, 2015).

Faced with such conditions, marginal households in rural areas have constrained ability to finance the uptake of recommended adaptation measures, modern strategies, while at the same time are destined to be poorly-served by institutional services either because majority of them lives in remote areas (Bett et al., 2017; Faisal et al., 2020) or are ignored deliberately. However, if they are able to access institutional services, their quality might be compromised, to the most extent, leading to adverse outcomes instead of any improvement thereof. In previous studies, adaptation to climate change mitigation strategies such as improved feeding practices (grazing management, diet supplementation, practicing concentrate and bran feeding), provision of medical facilities (disease control precaution, involvement in some sort of livestock training), updating with seasonal and weather forecast information, uptake of livestock diversification and improved/stress-tolerant breed/species, whether or not livestock herders formally adopted or not, have almost remained ignored to be explored. Therefore, it is vital to study all key factors that cause livestock losses and thus necessitate their mitigation either by the farmers themselves or institutional intervention for effective adaptation campaign (Kauppinen et al., 2012). Multivariate models are required to be used to quantify effect of these multiple factors, but insufficient data availability mar such analysis (Henry et al., 2012). In addition, the situation is further complicated vis-à-vis developing countries where limited knowledge prevails in terms of reliable long term climate and disease data, considerable influence from socioeconomic drivers and disease transmission mechanism (Patz et al., 2005). This situation has wide-ranging implications for developmental efforts by the governments and international community (Thornton et al., 2009). Nevertheless, it is pertinent to note that development in the livestock sector can have more favorable impacts on poverty reduction than the development in crop sector because livestock is more dispersed and less-associated with cultivated land (Bangalore et al., 2017).

It is crucial in the context of climate change to enhance adaptive capacity, governance structure, knowledge level, and adaptation itself to reduce adverse consequences by utilizing traditional ecological facts and customs of the inhabitants in that areas to cope with natural hazards (Byg and Salick, 2009). As such, an extensive range of choices are present, and livestock herders can choose those options whose dependence on accessibility and availability of resources is relatively less. However, developing countries' geographical locations and socio-economic conditions make them more vulnerable, while their constrained capabilities to mitigate these adverse effects mainly because of limited resource endowments exacerbate the situation (Maskrey et al., 2007). That is why poor people from rural areas are highly vulnerable because of insufficient ex-ante risk managing capability and ex-post coping capacity (Rahut and Ali, 2017; Faisal et al., 2021).

Policymakers and researchers stress that most substantial impact of climate change could be realized in livestock sector (Thornton et al., 2014), while, previously, most efforts have focused crop sector (Banik et al., 2015; Thornton and Gerber, 2010). Considering this research gap, the current study imparts a substantial contribution to the prevailing literature from three different viewpoints. First, identifying the factors that influence the small livestock herders' adoption decision in response to climate change. Second, how does climate change adaptation impact on livestock losses and poverty? Third, this study adds to the limited literature by providing some insights that could be useful in policymaking.

## 2. Conceptual framework and methodology

### 2.1. Conceptual framework

The conceptual framework of study is described in Fig. 1. In the present framework, climate change mitigation strategy is defined as

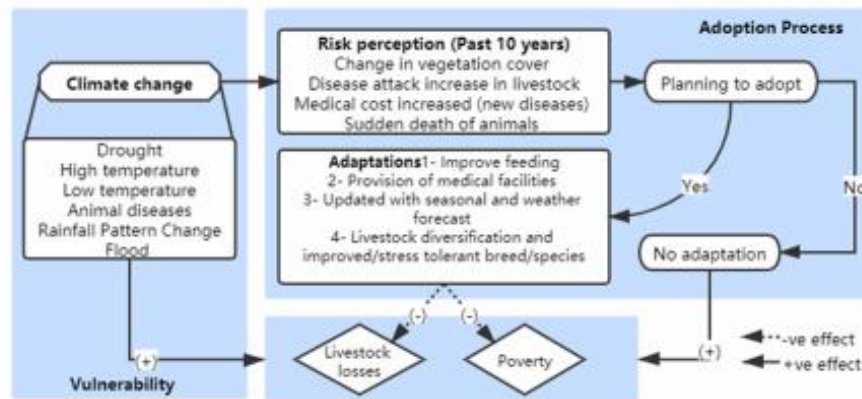


Fig. 1. Conceptual framework of the study.

adaptation to avoid livestock losses. A livestock herder will be considered as an adopter if s/he adopts a specific strategy and non-adopter if s/he does not adopt that strategy. By following previous studies (Abid et al., 2016; Liu et al., 2019; Mendola, 2007; Tessema et al., 2018) to model adaptation decisions of livestock herders, we employ a random utility framework. Here, we assume that  $i$ th livestock herder will choose to adopt a climate change mitigation strategy only if the expected net outcome is valuable. For example, reduction of livestock losses and improved well-being of livestock herders result in poverty reduction (Rahut and Ali, 2018; Liu et al., 2019; Mendola, 2007).

1iff  $\beta_i > 0$  and 0 if  $\beta_i \leq 0$

Here,  $\beta_i$  depicts that the  $i$ th livestock herder will adopt a climate change mitigation strategy ( $\beta_i = 1$ ), only if net benefits from adoption are positive ( $\beta_i > 0$ ), while the  $i$ th livestock herder will not adopt ( $\beta_i = 0$ ) if net benefits are non-positive ( $\beta_i \leq 0$ ).

Effective adaptation strategies could help to decrease livestock losses. However, it might be hard to distinguish between adopters and non-adopters on the basis of welfare. Contrasting with biological true experiment, social science experiments often face problems of randomness in the data, either in control or experiment groups. It would be quite easy to chalk out the differences between adopters and non-adopters if the data are collected through randomization and counterfactual situation (Rahut and Ali, 2017). As in our study, where no counterfactual information prevails for cross-sectional data, the direct impact of adaptation can be calculated by considering the differences in outcomes of adopters and non-adopters. But, it may result into misleading and biased estimates. The following equation is used for the estimates;

$$Y_{ik} = \alpha X_{ij} + \delta \beta_i + \epsilon_i \text{ while } \beta_i = \lambda X_{ij} + \mu_i, \text{ So } Y_{ik} = \alpha X_{ij} + \delta (\lambda X_{ij} + \mu_i) + \epsilon_i$$

Here,  $Y_{ik}$  is the vector of the outcome variable (livestock losses and poverty for the  $i$ th livestock herder) and the error term is  $\epsilon_i$ .  $\alpha$ ,  $\delta$  are the regression coefficient,  $X_{ij}$  represents the vector of independent variables and  $\lambda$  and  $\mu_i$  are respectively the logistic regression coefficient and its error term. It might be possible that the decision to adopt  $\beta_i$  is assumed to be independent, which may be influenced by some unknown factor(s) that form the error term  $\epsilon_i$ . Moreover  $\epsilon_i$  may be correlated with  $\mu_i$  leading to biased estimates due to selection bias.

In addition, Poisson model is used to discover the determinants of the number of strategies adopted by livestock herders. The dependent variable in this model was the total number of strategies adopted by livestock herders; while independent variables are age, education, experience, household type/size, off-farm income, distance to market, operational landholding, area under herd and availability/use of institutional services.

## 2.2. PSM (Propensity score matching)

PSM approach is applied to carry out empirical analysis for biasedness correction, which may arise due to systematic differences between two groups (adopters and non-adopters) of livestock herders. Unlike weak instruments assumption problems, the selection on observables assumption is no more restrictive in PSM, allowing instrumental variable approach with the cross-sectional data set (Bryan et al., 2013). It is extensively applied in impact assessment studies where the expected treated effect for the treated population is measured (Ali et al., 2016; Birtal et al., 2012; Iheke and Agodiye, 2016; Liu et al., 2019; Mango et al., 2017). To generate the condition of a randomized experiment, PSM applies un-confoundedness (absence of selection bias or conditional independence) assumption (Mendola, 2007), hence livestock herders' adoption is random and uncorrelated with livestock losses and poverty, once we control for other covariates. Contrasting with other parametric methods, PSM entails no assumption regarding functional form in postulating the relationship between outcomes and the related predictors. It compares the households with the same probability of adaptation strategy and also lessens the dimensionality of the conditioning problem (Benfica et al., 2019). The propensity score obtained from this conditional probability permits to identify similar households (Heckman and Navarro-Lozano, 2004). Following equation postulates PSM applied in this work.

$$p(X_{ij}) = Pr[\beta_i = 1 | X_{ij}] \quad (1)$$

Where  $p$  shows the propensity scores of pre-adaptation characteristics of  $X_{ij}$ ,  $Pr$  is the probability and  $\beta_i$  indicates the adaptation to climate change. The conditional distribution  $X_{ij}$  is similar to both adopters and non-adopters (Mendola, 2007). The impact of adaptation strategies on outcome variables is denoted in terms of ATT (average treatment effect on the treated) or ATE (average treatment effect) where, treatment means adaptation. The term ATE denotes the overall impact of adoption on the outcome variables by considering all respondents, while ATT measures the impact of adaptation on the outcome variables only for treated respondents (i.e., after matching) (Ali and Abdulai, 2010). As we are more interested in ATT, it can be calculated after the estimation of propensity scores as:

$$T = E\{Y_1 - Y_0 | \beta_i = 1\} = E\{Y_1 - Y_0 | \beta_i = 1, p(X)\} = E\{Y_1 | \beta_i = 1, p(X)\} - E\{Y_0 | \beta_i = 0, p(X)\} \quad (2)$$

Here  $T$  indicates the ATT and  $p(X)$  indicates the propensity scores,  $Y_1$  and  $Y_0$  show the values of outcome variables. For matching, we applied NNM (nearest neighbor matching) method, which selects individual cases from both groups as matching partners based on their closeness to each other. The closeness is identified with their propensity scores (Abid et al., 2016; Ali et al., 2018; Ali and Erenstein, 2017; Benfica et al., 2019; Liu et al., 2019; Mendola, 2007; Rahut and Ali, 2017). NNM method matches both groups and eliminates the unmatched cases (Smith and Todd, 2005). In another sense, we can say that ATT is attained after detecting the effect of selection bias (Liu et al., 2019).

Meanwhile, the headcount index is used to measure the population that is counted as poor.  $P = 1/N \sum_{i=1}^N I(y_i < z)$ ,  $y_i$  = income/expenditures,  $z$  = poverty line,  $N$  = total population, indicator function value is one if  $(y_i < z)$  and household considered as a poor, and 0 otherwise (Mendola, 2007).

### 2.3. Dependent variables

We inquired livestock herders' perceptions about climate change and the number of times they had met such climatic shocks (flood, drought, diseases, etc.) over the period of last ten years. According to their experiences, livestock herders were further asked to list climate change mitigation strategies they had recently adopted to respond climatic risks. Consistent with previous literature (Banik et al., 2015; de Lauwere et al., 2012; Herrero et al., 2012; Kauppinen et al., 2012; Martínez-García et al., 2013; Nardone et al., 2010; Rigolot et al., 2017; Thornton et al., 2015; Thornton, 2010; Thornton and Gerber, 2010; Thornton and Herrero, 2015), the most adopted strategies were asked. These variables are considered as dependent variables in logit analysis: 1) Improved feeding (grazing management, diet supplements, practising concentrate and bran feeding), 2) Provision of medical facilities (disease control precaution, involve in some kind of livestock training), 3) Updated with seasonal and weather forecast information, and 4) Uptake of livestock diversification and rearing of improved/stress-tolerant breed/species. Dependent variable is coded with 0 (not-adopted) and 1 (adopted).

### 2.4. Independent variables

Independent variables used in this study are: age, education, experience, household type and size, off-farm income, distance from market, operational land holding area under livestock-herd and the access to institutional services (Govt. veterinary center, livestock helpline, private doctor availability, satisfactory veterinary services, extension services, and credit availability). The reasons for their inclusion in the model are based on their expected/anticipated impact on the dependent variable(s) as well as the insights from earlier research work. For example, it was anticipated that older household heads would be more likely to prefer traditional practices and hence less likely to adopt climate change mitigation strategies (Ali et al., 2018; Rahut et al., 2017; Rahut and Ali, 2017). Education is most important especially for those matters which are complex to learn (Foster and Rosenzweig, 2010). The level of schooling is likely to affect adaptation responses (Tan, 2014). So, it is a valid assumption that livestock herders with better education would benefit from access to information. Adoption studies show a positive association between level of education and adoption behavior (Akhtar et al., 2019, 2018; Permadi et al., 2018), but show a different viewpoint on the effect of age (Akudugu et al., 2012; Uaiene, 2008). Education is also considered as a substitute to experience. However, it is expected to have a positive association with livestock herders' probability of adopting climate change mitigation strategies. As consistent with previous studies (Akhtar et al., 2019, 2018; Bastakoti et al., 2014; Raza et al., 2019), adopters are shown to have more education and experience being more observant and better informed about continued variations in the environment and thus lead them to effective adaptation practices in comparison with non-adopters. We thus posit/expect a positive association between the level of schooling and adaptation but are uncertain on age. Nevertheless, more-experienced farmers are expected to possess greater level of local and informal knowledge which is generally different from formal education and hence can have contrasting outcomes in the uptake of climate change mitigation options.

There exists a varying opinion as well as indeterminate association of adaptation actions vis-à-vis household type and size, operational land holding area and distance to market (access to market) (Mulwa et al., 2017; Tessema et al., 2018). Better access to labour and resources are generally proxied/represented by household size and landholding (Tessema et al., 2018). However, access to the market can be interrelated with access to information and cost-effective adjustments (Mulwa et al., 2017). Therefore, it is anticipated that market access influences all categories of adaptation. We anticipate that livestock herders' off-farm work has a negative influence on adaptation because it would reduce time. However, off-farm participation is shown to increase adoption trends (Akhtar et al., 2019), although Diro (2013) shows an otherwise findings. In other sense, the relationship between off-farm income and adaptation is somewhat indeterminate.

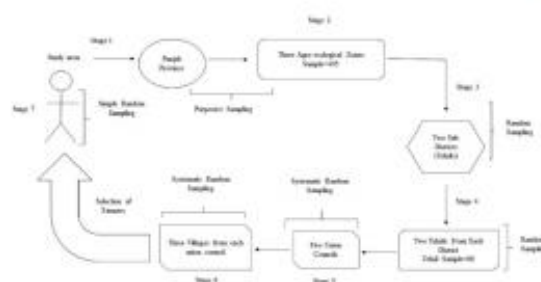


Fig. 2. Data collection framework and Sampling technique

**Table 1**  
Climate characteristics of the study area (2010–2019).

| Area                   | Agro-ecological zone | Annual Min. Temp. °C (mean) | Annual Max. Temp. °C (mean) | Annual rainfall millimeter (mm) |
|------------------------|----------------------|-----------------------------|-----------------------------|---------------------------------|
| Dera Ghazi Khan (DGK)  | Low-intensity        | 18.77                       | 32.34                       | 248.98                          |
| Rahim Yar Khan (RYK)   | Cotton-wheat         | 18.98                       | 34.41                       | 143.43                          |
| Faisalabad (Fsd)       | Mixed cropping       | 18.01                       | 30.99                       | 434                             |
| Average of three zones |                      | 18.58667                    | 32.58                       | 275.47                          |

Source: Pakistan meteorological department.

The campaigns on climate change mitigation strategies has been essential for public institutional system (Abate et al., 2015; Berhanu and Poulton, 2014), but such information has been reported to be very inadequate in developing countries (Deressa et al., 2011; Thornton et al., 2014; Thornton et al., 2009). We posit that adopters have more access to institutional services (Govt. veterinary center, livestock helpline, private doctor availability, satisfactory veterinary services, extension services, and credit availability) resulting in greater association with the probability of adopting climate change mitigation strategies (Thornton et al., 2015). In general, institutional services are meant for informing livestock herders with new strategies along with associated costs/benefits and risks. Access to institutional services is directly related to information access regarding several issues including climate change mitigation strategies and therefore, a positive relationship is predicted (Akhtar et al., 2018; Rahut and Ali, 2018; Bastakoti et al., 2014; Bryan et al., 2013; Simtowe and Zeller, 2007). However, livestock herders are comparatively less resource-intensive and it is anticipated that access to institutional services will impart more obvious effect (Bastakoti et al., 2014).

### 2.5. Participants, data collection technique and climate indicators of the region

Multistage sampling technique (District → Tehsil → Union council → Villages → Respondents) was used for field research to collect primary data from three different zones (based on geography, climate and cropping pattern) of the Punjab province of Pakistan. The sampling technique was followed from recently-published literature (Akhtar et al., 2021; Faisal et al., 2021; Faisal et al., 2020). From each zone, one district was selected: First, Dera Ghazi Khan (from low-intensity zone), second, Rahimyar Khan (from cotton-wheat zone), third, Faisalabad (from mixed cropping zone). In these three districts, sheep, cattle, goat, buffalo, and camel population is dominant compared with rest of the province (GOP, 2018). For the precision of collected data, face-to-face interviews were executed because of the low literacy rate among livestock herders. For data collection, we sought the help from extension officers within the respective districts and enquired the list of livestock herders. Thereafter, the sample of small livestock herders who raised animals in their homes for livelihood was drawn from their pre-prepared list. Livestock herders were interviewed by the trained interviewers. Data collection was completed from 1st January 2019 to 30th June 2019. In total, 405 smallholder livestock herders' data collected from the study area. The research sampling technique of this study is presented in Fig. 2.

The specific climate-related characteristics of the selected agro-ecological zones for the period 2010–2019 derived from the processing of meteorological data are portrayed in Table 1. These zones are characterized by a mean annual temperature in the range of around 18.6–32.6 °C while the total annual rainfall in the range of 143 mm to 434 mm over aforesaid period.

### 3. Results and discussions

### 3.1. Descriptive statistics

Table 2 shows the descriptive statistics of the variables used in our study. The results show that the average age of livestock herders was 44 years, while livestock rearing experience was 22 years. It indicates that middle-aged livestock herders had a considerable amount of livestock rearing experience. The average number of household members was 9.94, which indicates that family size was moderately large because 63% of respondents were living in joint/extended type of family system. As mentioned above, the sampled households were involved in livestock rearing activity. The mean area under livestock herd was 6.67 Marla and the operational land

**Table 2**  
Descriptive statistics of variables.

| Variable                                                                                                                                                                                                                               | Variable description                                         | Std. Dev. | Mean   |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------|-----------|--------|
| <b>Independent variable</b>                                                                                                                                                                                                            |                                                              |           |        |
| Age                                                                                                                                                                                                                                    | Continuous variable (Years)                                  | 11.147    | 44.395 |
| Education                                                                                                                                                                                                                              | Continuous variable (Years)                                  | 4.486     | 5.506  |
| Experience                                                                                                                                                                                                                             | Continuous variable (Years)                                  | 10.486    | 22.047 |
| Household type                                                                                                                                                                                                                         | 1 if joint family, 0 otherwise                               | 0.484     | 0.630  |
| Household size                                                                                                                                                                                                                         | Total no. of members                                         | 7.510     | 9.943  |
| Off-farm income                                                                                                                                                                                                                        | 1 if household have off-farm work, 0 otherwise               | 0.485     | 0.622  |
| Distance to market                                                                                                                                                                                                                     | Main market distance from respondent home (Km)               | 7.846     | 15.521 |
| Operational landholding                                                                                                                                                                                                                | Acres                                                        | 12.333    | 8.718  |
| Area under-heard                                                                                                                                                                                                                       | Marla                                                        | 7.517     | 6.679  |
| Govt. veterinary center                                                                                                                                                                                                                | 1 if the village has such facility, 0 otherwise              | 0.496     | 0.568  |
| Livestock helpline                                                                                                                                                                                                                     | 1 if benefited from that service, 0 otherwise                | 0.381     | 0.175  |
| Private doctor availability                                                                                                                                                                                                            | 1 if private veterinary doctor available, 0 otherwise        | 0.485     | 0.625  |
| Satisfactory veterinary facilities                                                                                                                                                                                                     | 1 if satisfactory veterinary services available, 0 otherwise | 0.495     | 0.578  |
| Extension services                                                                                                                                                                                                                     | 1 if livestock herder has access, 0 otherwise                | 0.491     | 0.600  |
| Credit availability                                                                                                                                                                                                                    | 1 if livestock herder has access, 0 otherwise                | 0.494     | 0.420  |
| <b>Dependent variables (adaptation: 1 if adopted, 0 otherwise)</b>                                                                                                                                                                     |                                                              |           |        |
| 1) Improved feeding (grazing management, diet supplements, practicing concentrate and bran feeding)                                                                                                                                    |                                                              | 0.495     | 0.573  |
| 2) Provision of medical facilities (disease control precaution, involve in some kind of livestock training)                                                                                                                            |                                                              | 0.424     | 0.235  |
| 3) Updated with seasonal and weather forecast information                                                                                                                                                                              |                                                              | 0.453     | 0.286  |
| 4) Livestock diversification and improved/stress tolerant breed/species                                                                                                                                                                |                                                              | 0.374     | 0.168  |
| <b>Outcome variables</b>                                                                                                                                                                                                               |                                                              |           |        |
| Livestock losses                                                                                                                                                                                                                       | Past one-year livestock losses (Numbers)                     | 0.731     | 0.770  |
| Poor (Head count index)                                                                                                                                                                                                                | 1 if poor, 0 otherwise                                       | 0.500     | 0.519  |
| <b>Other climate related risk perceptions of livestock herders (not used in empirical analysis)</b>                                                                                                                                    |                                                              |           |        |
| Have you observed any change in vegetation cover over the last 10 years?                                                                                                                                                               |                                                              |           | 0.56   |
| Have you observed any disease attack increase in livestock over the last 10 years?                                                                                                                                                     |                                                              |           | 0.64   |
| Do you think livestock medical cost increased because of new diseases                                                                                                                                                                  |                                                              |           | 0.59   |
| Do you think the sudden death of animals increased in the past 10 years                                                                                                                                                                |                                                              |           | 0.38   |
| Livestock diseases in study area: foot and mouth disease (9.9%), haemorrhagic septicaemia (8.1%), black quarter (15.8%), PPR (1.5%), and rinderpest (2.2%). Don't know disease name (19.3%), have no experience of any disease (43.2%) |                                                              |           |        |

holdings were 8.71 acres. About 56.8% of the respondents had Govt. veterinary center facility, 57.8% of livestock herders testified satisfaction from veterinary services, and only 17.5% got benefit from livestock helpline. Moreover, approximately 62.5% of the livestock herders had private doctor availability. Several questions associated with the issue of climate change and relevant mitigation strategies were incorporated in the questionnaire. However, respondents in the study area generally adapted four major strategies: 1) Improved feeding (grazing management, diet supplements, practicing concentrate and bran feeding) (57.3%), 2) provision of medical facilities (disease control precaution, involve in some kind of livestock training) (23.5%), 3) updated with seasonal and weather forecast information (28.6%), 4) uptake of livestock diversification and improved/stress-tolerant breed/species (16.8%). According to livestock herders, the severe climatic conditions have resulted in livestock losses. The most common diseases in the study areas are foot and mouth, haemorrhagic septicaemia, black quarter, PPR, and rinderpest (local names of these diseases: *mohara*, *gul ghoton*, *zahr baad*, *katta*, *maata*, respectively). Most of the respondents were unaware about which kind of disease led to the death of their animals. Results in Table 2 also indicate the perceived risk intensity and it is clear majority of the farmers have reported an increase in all four risk indicators over the past 10 years. For example, 64% and 59% respondents report an increase in livestock diseases and increased medical cost due to disease attack, respectively, in the past 10 years. Moreover, 38% herders report an increase in sudden death of animals during this period.

### 3.2. Determinants of the number of strategies adopted by livestock herders

Poisson model is used to discover the determinants of the number of strategies adopted by livestock herders. The model results are shown in Table 3. The dependent variable in this model was the total number of strategies adopted by livestock herders; while independent variables are listed in Table 2. In model results, the age coefficient is significant and negative, depicting that younger livestock herders normally adopt more climate change mitigation strategies. The coefficient of education and experience is positive and highly significant, emphasizing the reality that educated livestock herders would likely adopt more strategies. The coefficient of family type is significant and positive, depicting that livestock herders living in a joint/extended family type would be tempted to adopt more strategies. The reason for this result might be that joint families have excess labour who is obliged to look after their livestock. Moreover, the result of family size is significant and positive and is consistent with family type results, which depicts that households with more family members adopt more climate change mitigation strategies because of the availability of manpower needed to manage the livestock. Distance to market, operational landholding and area under-heard are non-significant, implying that these do not affect respondents' adoption behaviour regarding climate change mitigation strategies. The coefficient of off-farm work is

**Table 3**  
Determinants of adopted strategies by livestock herders.

| Variables                          | Poisson estimates                             |         | PSM estimates                             |                                           |           |                                           |           |                                           |           |         |
|------------------------------------|-----------------------------------------------|---------|-------------------------------------------|-------------------------------------------|-----------|-------------------------------------------|-----------|-------------------------------------------|-----------|---------|
|                                    | Adopted strategies<br>Coefficient (Std. Err.) |         | 1 <sup>a</sup><br>Coefficient (Std. Err.) | 2 <sup>b</sup><br>Coefficient (Std. Err.) |           | 3 <sup>c</sup><br>Coefficient (Std. Err.) |           | 4 <sup>d</sup><br>Coefficient (Std. Err.) |           |         |
| Age                                | -0.015**                                      | (0.008) | -0.017                                    | (0.016)                                   | -0.047*   | (0.027)                                   | -0.024    | (0.026)                                   | -0.063*   | (0.034) |
| Education                          | 0.055***                                      | (0.013) | 0.038                                     | (0.034)                                   | 0.200***  | (0.045)                                   | 0.184***  | (0.043)                                   | 0.076     | (0.049) |
| Experience                         | 0.018**                                       | (0.008) | 0.036**                                   | (0.017)                                   | 0.042     | (0.027)                                   | 0.030     | (0.027)                                   | 0.055     | (0.035) |
| Household type                     | 0.355***                                      | (0.108) | 0.696***                                  | (0.249)                                   | 0.828**   | (0.340)                                   | 0.803**   | (0.327)                                   | 0.262     | (0.406) |
| Household size                     | 0.009*                                        | (0.005) | 0.056**                                   | (0.026)                                   | 0.017     | (0.018)                                   | 0.017     | (0.019)                                   | 0.034     | (0.022) |
| Off farm income                    | -0.227**                                      | (0.109) | -0.236                                    | (0.286)                                   | -0.739**  | (0.361)                                   | -0.476    | (0.362)                                   | -0.937**  | (0.447) |
| Distance to market                 | -0.005                                        | (0.007) | -0.002                                    | (0.019)                                   | -0.019    | (0.022)                                   | -0.034    | (0.022)                                   | -0.028    | (0.027) |
| Operational land holding           | 0.003                                         | (0.004) | 0.019                                     | (0.013)                                   | -0.003    | (0.014)                                   | 0.003     | (0.014)                                   | 0.007     | (0.017) |
| Area under heard                   | -0.005                                        | (0.008) | 0.025                                     | (0.033)                                   | -0.055*   | (0.031)                                   | 0.045     | (0.035)                                   | 0.065*    | (0.039) |
| Govt. veterinary center            | 0.238**                                       | (0.106) | 0.313                                     | (0.252)                                   | 0.489     | (0.332)                                   | 1.017***  | (0.329)                                   | 0.698*    | (0.404) |
| Livestock helpline                 | 0.502***                                      | (0.176) | 0.543                                     | (0.525)                                   | 1.821**   | (0.574)                                   | 0.325     | (0.573)                                   | 1.001     | (0.636) |
| Private doctor availability        | 0.399***                                      | (0.127) | 0.450                                     | (0.285)                                   | 0.484     | (0.398)                                   | 0.893**   | (0.390)                                   | 1.340**   | (0.535) |
| Satisfactory veterinary facilities | 0.373***                                      | (0.119) | 0.696**                                   | (0.282)                                   | 0.507     | (0.365)                                   | 0.563     | (0.362)                                   | 1.610***  | (0.509) |
| Extension services                 | 0.650***                                      | (0.121) | 0.789***                                  | (0.257)                                   | 1.637***  | (0.384)                                   | 1.362***  | (0.358)                                   | 2.335***  | (0.566) |
| Credit availability                | 0.010                                         | (0.111) | -0.625**                                  | (0.288)                                   | 0.504     | (0.358)                                   | 0.595*    | (0.346)                                   | -0.046    | (0.416) |
| Dera Ghazi Khan                    | 0.157                                         | (0.146) | 0.100                                     | (0.362)                                   | 2.084***  | (0.507)                                   | -0.322    | (0.464)                                   | -0.671    | (0.576) |
| Rahim Yar Khan                     | -0.056                                        | (0.137) | -0.372                                    | (0.368)                                   | 1.057**   | (0.464)                                   | -1.029**  | (0.457)                                   | -1.212**  | (0.536) |
| Faisalabad                         | (omitted)                                     |         | (omitted)                                 |                                           | (omitted) |                                           | (omitted) |                                           | (omitted) |         |
| Constant                           | -1.303***                                     | (0.342) | -2.074***                                 | (0.791)                                   | -4.842*** | (1.086)                                   | -4.516*** | (1.085)                                   | -4.892*** | (1.377) |
| Log pseudo likelihood              | -492.337                                      |         | -224.658                                  |                                           | -150.785  |                                           | -156.295  |                                           | -115.446  |         |
| Wald chi2                          | 253.470                                       |         | 103.510                                   |                                           | 139.670   |                                           | 172.530   |                                           | 135.670   |         |
| Pseudo R <sup>2</sup>              | 0.205                                         |         | 0.187                                     |                                           | 0.317     |                                           | 0.356     |                                           | 0.370     |         |

Note: \* 10%, \*\* 5% and \*\*\*1%.

<sup>a</sup> Improve feeding (grazing management, diet supplementation, practicing concentrate and bran feeding).

<sup>b</sup> Provision of medical facilities (disease control precaution, involve in some kind livestock training).

<sup>c</sup> Updated with seasonal and weather forecast information.

<sup>d</sup> Livestock diversification and improved/stress-tolerant breed/species.

negative and significant thus having a great influence on adaptation indicating that off-farm work would reduce time allocated for livestock upkeep. Moreover, the variables on institutional services (Govt. veterinary center, livestock helpline, private doctor availability, satisfactory veterinary services and extension services) are positive and highly significant except credit availability, which may be linked with access to information. Above mentioned outcomes are aligned with previous studies (Rahut and Ali, 2018; Ali and Rahut, 2018).

### 3.3. Propensity score estimates

The matching process was performed with the estimation of propensity scores for the treatment variable. The logistic model was used for this purpose, where the probability of adopting a climate change mitigation strategies was regressed one by one with covariates. The outcome of estimates of propensity scores is shown in Table 3. Our findings for all four adaptation strategies are mostly similar to Poisson regression estimates. Our dependent variables are defined as 1) Improved feeding (grazing management, diet supplements, practicing concentrate and bran feeding), 2) Provision of medical facilities (disease control precaution, involve in some kind of livestock training), 3) Updated with seasonal and weather forecast information, 4) Uptake of livestock diversification and improved/stress-tolerant breed/species, whether or not livestock herders formally adopted some strategy for their livestock. The results depict that covariates influence the probability of adaptation of climate change strategies. In the 2nd and 4<sup>th</sup> strategy, the age coefficient is negative and significant, depicting that young livestock herders adapt these strategies to mitigate climatic risk impact on livestock. Particularly, experience, education, household type/size, and institutional services have positive coefficients and tend to accelerate adaptation. More experience, knowledge, awareness about climate change force them to adopt favourable strategies. These outcomes confirm our anticipations and are consistent with other studies' findings (Bryan et al., 2009; Deressa et al., 2011; Nabikolo et al., 2012; Yu et al., 2010).

The institutional services' (Govt. veterinary center, livestock helpline, private doctor availability, satisfactory veterinary services and extension services) coefficients are positive and significant in maximum adaptation strategies. However, off-farm income and credit availability have a negative coefficient. Contrasting with some other studies findings (Ibeke and Agodiye, 2016), a negative coefficient indicates that livestock herders are less likely to adopt these because of limited time and limited access to information (Abid et al., 2016). Regional dummies' negative coefficients of Dera Ghazi Khan and Rahimyar Khan indicate that livestock herders are less likely to adopt climate change mitigation strategies as compared to the livestock herders located in Faisalabad district. This depicts that livestock herders located in Faisalabad are more anxious about climate change. These options are highly relevant for the improvement of livestock sector for the region as evinced by Banik et al., 2015; Thomson et al., 2014. Not surprisingly, study reveals some critical

**Table 4**  
Adaptation strategies impact on livestock losses and poverty.

| Adopted Strategies | Outcome          | ATT       | Std. Err. | No. of treated | No. of control |
|--------------------|------------------|-----------|-----------|----------------|----------------|
| 1                  | Livestock losses | -0.301**  | 0.136     | 229            | 173            |
|                    | Poverty          | -0.218**  | 0.095     | 229            | 173            |
| 2                  | Livestock losses | -0.484*** | 0.146     | 93             | 217            |
|                    | Poverty          | -0.204**  | 0.090     | 93             | 217            |
| 3                  | Livestock losses | -0.314**  | 0.136     | 105            | 225            |
|                    | Poverty          | -0.229**  | 0.097     | 105            | 225            |
| 4                  | Livestock losses | -0.328**  | 0.151     | 64             | 171            |
|                    | Poverty          | -0.047    | 0.110     | 64             | 171            |

Note: \* 10%, \*\* 5% and \*\*\* 1%.

**Table 5**  
Covariates balancing indicators.

| Adaptation | Sample    | Ps R2 | LR chi2 | p > chi2 | Mean Bias | Med Bias | B      |
|------------|-----------|-------|---------|----------|-----------|----------|--------|
| 1          | Unmatched | 0.185 | 102.40  | 0.000    | 30.4      | 34.4     | 108.9* |
|            | Matched   | 0.084 | 53.20   | 0.023    | 18.3      | 15.0     | 70.5*  |
| 2          | Unmatched | 0.318 | 140.13  | 0.000    | 39.4      | 38.9     | 158.9* |
|            | Matched   | 0.062 | 15.99   | 0.524    | 10.1      | 7.3      | 59.4*  |
| 3          | Unmatched | 0.358 | 173.58  | 0.000    | 46.4      | 42.0     | 168.6* |
|            | Matched   | 0.086 | 24.90   | 0.097    | 14.7      | 11.9     | 70.5*  |
| 4          | Unmatched | 0.373 | 136.81  | 0.000    | 47.7      | 41.7     | 177.1* |
|            | Matched   | 0.144 | 25.63   | 0.081    | 14.6      | 14.0     | 93.6*  |

factors considered to be essential to facilitate adaptation process in rural areas especially related to livestock sector. These include age, education, experience and access to institutional services. These findings are in line with the results of [Abid et al. \(2016\)](#) and [Rahut and Ali \(2018\)](#). Although there exists a significant correlation between variables, we are restricted in terms of inferring causality, which comes from potential self-selection and heterogeneity. Thus PSM is used to correct for any selection bias in the model.

Estimates of propensity scores used to assess the impact of adoption strategies on livestock losses and poverty. We used NNM to demonstrate the matching effect, which was established on similar propensity scores. After the accomplishment of PSM, we found a similar density of propensity scores between the two groups. NNM removes the unmatched non-adopters during the matching process, results in a reduction in sample size for impact analysis in post-matching. Then, sample characteristics reasonably comparable in the treatment and control group for the calculation of average adaptation impact on livestock losses and poverty.

#### 3.4. ATT effect of adaptation on livestock losses and poverty

Using PSM analysis, ATT indicates the difference in outcome for the livestock herders between two groups. We combined three matching methods (NNM, kernel-based matching, and radius matching) to calculate ATT. The results of the NNM are shown in [Table 4](#). The significant results of ATT show that adaptation does have a considerable impact on the reduction of livestock losses and poverty. The results for livestock losses and poverty are significant and negative, depicting that livestock losses and poverty index are lowered to the tune of 30–48% and 4–22%, respectively for those livestock herders who adopted the climate change mitigation strategies. For adopters, reduction livestock losses and poverty also depicts a positive impact of adaptation on overall well-being of livestock herders'. These findings are in line with previous studies ([Abid et al., 2016](#); [Liu et al., 2019](#); [Mendola, 2007](#)).

#### 3.5. Balance test

The main task of PSM is to develop a balance test to assess the matching effect (mean/median absolute bias, the value of  $R^2$  etc.) in our model that creates a balance between two groups. Balance test outcomes are shown in [Table 5](#). The absolute mean/median bias and the value of  $R^2$  were considerably reduced after matching, demonstrating that both groups are similar to each other after matching. As mentioned in results, the matching bias dropped after matching, which shows that there is no systematic difference between the two groups' (adopter and non-adopters) covariate distribution after matching. However, there exists a difference in the outcome that would only be due to adaptation. Moreover, results are significant before matching, and when matching is performed, variables are no longer significant or become less significant. The complete results for the balance test are shown in [Table 6](#). This is quite clear that our model corrected selection bias and well-matched the covariates with adaptation decisions.

**Table 6**  
The results of the balance test between treatment and control group.

| Variable <sup>e</sup> | Balance test |         |       |         | 1 <sup>a</sup> |      |   |          | 2 <sup>b</sup> |         |        |      | 3 <sup>c</sup> |          |       |         | 4 <sup>d</sup> |      |   |          |
|-----------------------|--------------|---------|-------|---------|----------------|------|---|----------|----------------|---------|--------|------|----------------|----------|-------|---------|----------------|------|---|----------|
|                       | Unmatched    | Matched | Mean  | Control | Reduce         | Bias | % | T-test   | Mean           | Control | Reduce | Bias | %              | T-test   | Mean  | Control | Reduce         | Bias | % | T-test   |
|                       |              |         |       |         |                |      |   |          |                |         |        |      |                |          |       |         |                |      |   |          |
| 1                     | U            | U       | 43.94 | 45.01   | -153.20        |      |   | -0.96    | 41.66          | 45.23   | 87.00  |      |                | -2.75*** | 41.82 | 45.43   | 74.90          |      |   | -2.91*** |
|                       | M            | M       | 43.89 | 41.16   |                |      |   | 2.74***  | 41.79          | 42.25   |        |      |                | -0.32    | 42.13 | 41.23   |                |      |   | 1.33     |
| 2                     | U            | U       | 6.43  | 4.27    | -1.90          |      |   | 4.94***  | 8.11           | 4.71    | 80.70  |      |                | 6.81***  | 8.75  | 4.20    | 78.80          |      |   | 6.32***  |
|                       | M            | M       | 6.47  | 8.68    |                |      |   | -4.82*** | 8.02           | 8.68    |        |      |                | -1.07    | 8.49  | 9.45    |                |      |   | -2.87    |
| 3                     | U            | U       | 22.65 | 21.24   | -89.40         |      |   | 1.33     | 21.13          | 22.33   | -20.70 |      |                | -0.98    | 21.00 | 22.47   | 67.50          |      |   | -1.19    |
|                       | M            | M       | 22.62 | 19.96   |                |      |   | 2.96***  | 21.18          | 22.63   |        |      |                | -1.05    | 21.16 | 20.69   |                |      |   | 2.41**   |
| 4                     | U            | U       | 0.72  | 0.51    | 79.30          |      |   | 4.45***  | 0.77           | 0.59    | 46.60  |      |                | 3.24***  | 0.79  | 0.56    | 87.50          |      |   | 2.82***  |
|                       | M            | M       | 0.72  | 0.76    |                |      |   | -1.07    | 0.76           | 0.67    |        |      |                | 1.46     | 0.78  | 0.81    |                |      |   | -0.90    |
| 5                     | U            | U       | 11.26 | 8.18    | 23.90          |      |   | 4.16***  | 12.99          | 9.01    | 96.80  |      |                | 4.63***  | 12.17 | 9.05    | 98.20          |      |   | 3.59***  |
|                       | M            | M       | 10.95 | 8.61    |                |      |   | 3.57***  | 12.93          | 13.05   |        |      |                | -0.08    | 11.77 | 11.71   |                |      |   | -0.70    |
| 6                     | U            | U       | 0.69  | 0.54    | 37.90          |      |   | 3.06***  | 0.67           | 0.61    | -59.90 |      |                | 1.18     | 0.74  | 0.57    | 43.00          |      |   | 1.84*    |
|                       | M            | M       | 0.69  | 0.78    |                |      |   | -2.22**  | 0.68           | 0.78    |        |      |                | -1.66    | 0.73  | 0.83    |                |      |   | -1.28    |
| 7                     | U            | U       | 16.07 | 14.79   | 68.40          |      |   | 1.62     | 14.93          | 15.70   | 50.20  |      |                | -0.84    | 16.42 | 15.16   | -3.30          |      |   | 1.61     |
|                       | M            | M       | 16.07 | 16.47   |                |      |   | -0.51    | 15.02          | 14.63   |        |      |                | 0.33     | 16.90 | 18.20   |                |      |   | 1.27     |
| 8                     | U            | U       | 10.68 | 6.09    | 78.20          |      |   | 3.77***  | 13.45          | 7.27    | 94.60  |      |                | 4.36***  | 12.88 | 7.05    | 68.30          |      |   | 3.26***  |
|                       | M            | M       | 10.38 | 9.38    |                |      |   | 0.83     | 13.28          | 12.95   |        |      |                | 0.16     | 11.58 | 9.73    |                |      |   | -1.04    |
| 9                     | U            | U       | 8.09  | 4.78    | 82.20          |      |   | 4.69***  | 8.77           | 6.04    | 80.30  |      |                | 3.13***  | 9.39  | 5.59    | 86.70          |      |   | 7.27***  |
|                       | M            | M       | 7.85  | 8.44    |                |      |   | -0.84    | 8.88           | 9.42    |        |      |                | -0.40    | 7.93  | 7.43    |                |      |   | 0.69     |
| 10                    | U            | U       | 0.63  | 0.49    | 15.10          |      |   | 2.70***  | 0.74           | 0.52    | 95.10  |      |                | 3.86***  | 0.76  | 0.49    | 100.00         |      |   | 3.64***  |
|                       | M            | M       | 0.62  | 0.51    |                |      |   | 2.46**   | 0.73           | 0.74    |        |      |                | -0.17    | 0.74  | 0.74    |                |      |   | 0.40     |
| 11                    | U            | U       | 0.24  | 0.09    | 94.00          |      |   | 3.84***  | 0.29           | 0.14    | 100.00 |      |                | 3.54***  | 0.28  | 0.13    | 93.80          |      |   | 5.84***  |
|                       | M            | M       | 0.23  | 0.24    |                |      |   | -0.22    | 0.30           | 0.30    |        |      |                | 0.00     | 0.24  | 0.23    |                |      |   | 0.00     |
| 12                    | U            | U       | 0.73  | 0.48    | 79.30          |      |   | 5.37***  | 0.78           | 0.58    | 41.30  |      |                | 3.60***  | 0.84  | 0.54    | 72.20          |      |   | 5.24***  |
|                       | M            | M       | 0.73  | 0.79    |                |      |   | -1.31    | 0.78           | 0.90    |        |      |                | -2.24*   | 0.83  | 0.91    |                |      |   | 0.27     |
| 13                    | U            | U       | 0.68  | 0.44    | 83.70          |      |   | 5.01***  | 0.79           | 0.51    | 88.30  |      |                | 4.90***  | 0.81  | 0.46    | 62.00          |      |   | 5.79***  |
|                       | M            | M       | 0.68  | 0.72    |                |      |   | -0.92    | 0.78           | 0.82    |        |      |                | -0.55    | 0.80  | 0.68    |                |      |   | 0.51     |
| 14                    | U            | U       | 0.72  | 0.44    | 84.40          |      |   | 5.93***  | 0.86           | 0.52    | 90.60  |      |                | 6.25***  | 0.84  | 0.50    | 55.60          |      |   | 6.30***  |
|                       | M            | M       | 0.72  | 0.76    |                |      |   | -1.07    | 0.86           | 0.89    |        |      |                | -0.67    | 0.83  | 0.68    |                |      |   | 0.00     |
| 15                    | U            | U       | 0.44  | 0.39    | 53.80          |      |   | 1.14     | 0.60           | 0.36    | 77.20  |      |                | 4.14***  | 0.59  | 0.35    | 84.50          |      |   | 2.56**   |
|                       | M            | M       | 0.44  | 0.41    |                |      |   | 0.57     | 0.59           | 0.65    |        |      |                | -0.75    | 0.55  | 0.51    |                |      |   | -0.53    |
| 16                    | U            | U       | 0.33  | 0.34    | -679.00        |      |   | -0.28    | 0.44           | 0.30    | 47.00  |      |                | 2.59***  | 0.30  | 0.35    | 35.50          |      |   | -1.32    |
|                       | M            | M       | 0.32  | 0.22    |                |      |   | 2.54**   | 0.43           | 0.35    |        |      |                | 1.05     | 0.27  | 0.24    |                |      |   | -0.21    |
| 17                    | U            | U       | 0.32  | 0.35    | -345.10        |      |   | -0.50    | 0.32           | 0.34    | 53.10  |      |                | -0.41    | 0.25  | 0.37    | -14.20         |      |   | -0.47    |
|                       | M            | M       | 0.33  | 0.22    |                |      |   | 2.52**   | 0.32           | 0.33    |        |      |                | -0.16    | 0.28  | 0.14    |                |      |   | 1.18     |
| 18                    | U            | U       | 0.35  | 0.31    | -666.50        |      |   | 0.78     | 0.24           | 0.36    | 45.90  |      |                | -2.16**  | 0.45  | 0.29    | -0.50          |      |   | 1.79*    |
|                       | M            | M       | 0.35  | 0.56    |                |      |   | -4.60*** | 0.25           | 0.31    |        |      |                | -0.98    | 0.46  | 0.62    |                |      |   | -0.88    |

<sup>a</sup> Improved feeding (grazing management, diet supplementation, picking concentrate and bran feeding), <sup>b</sup> Provision of medical facilities (disease control precaution, involve in some kind livestock training), <sup>c</sup> Upward with seasonal and weather forecast information, <sup>d</sup> Livestock diversification and improved/stress-tolerant breed/species, <sup>e</sup> (1 = Age, 2 = Education, 3 = Experience, 4 = Household type, 5 = Household size, 6 = Off-farm income, 7 = Distance to market, 8 = Area under-land, 9 = Operational landholding, 10 = Govt. veterinary center, 11 = Livestock helpline, 12 = Private doctor availability, 13 = Satisfactory veterinary facilities, 14 = Extension services, 15 = Credit availability, 16 = Deen Ghaat Khan, 17 = Rahim Yar Khan, 18 = Faisalabad), Note: \* 10%, \*\* 5% and \*\*\*1%.

#### 4. Conclusion and policy suggestions

It is projected that climate change will have an adverse impact on livestock and rural livelihood in Pakistan. Few studies have been undertaken about climate change adaptation' impact on the reduction of livestock losses and poverty. Taking a sample of three districts within Punjab province of Pakistan, this study provides valuable insights for future adaptation planning and policy formulation. The main adaptation measures across three regions include, improved feeding (grazing management, diet supplements, practicing concentrate and bran feeding), provision of medical facilities (disease control precaution, involve in some kind of livestock training), updated with seasonal and weather forecast information, livestock diversification and improved/stress-tolerant breed/species. It is concluded that adaptations are most desirable to lessen the potential losses brought about by climate changes. However, these mitigation strategies, livestock losses, and poverty are so complex and we do not claim to have comprehensively captured them all. We elaborated adaptation of each strategy's impact independently but in reality, these interrelate in numerous ways with each other and with other potential options not covered by this study. It is pertinent to mention that there is range of options to counter livestock losses but the four strategies chosen in this study are based on their vast uptake. These strategies, however, can go futile or less-effective if concrete measures and climate adaptation plans are not fully operationalized at the national level. This is because one locality in a vast geographical setting resorting to environmentally-friendly production and consumption would see it nowhere if policy fails to popularize such options on a larger scale. Many of the outcomes of most-popular mitigation options need proper frameworks for input procurement and output disposal. Any market failure can potentially lead to catastrophic economic consequences for the adopters of eco-friendly and/or climate-change mitigating options. Furthermore, these adaptation decisions are considerably affected by numerous external and internal factors. However, poor societies have limited resources to invest in these desirable adaptations and also poorly served by institutional services (extension services, veterinary facilities, knowledge of diseases, etc.) because they live in remote areas. Though, our PSM estimation analysis highlights that there exists a massive potential for reducing these losses through the adoption of these strategies, which will result in the enhancement of livestock herders' productive capacity. The outcome of this study offers, better targeting investigation on resource-poor personnel which might be the main vehicle for reducing livestock losses and maximizing direct poverty alleviation.

Creating an explicit reference to the fundamental relationship between adaptation strategies and livestock herders' well-being, in our study, we try to find out the answer to counterfactual questions that are most important for the formulation of favourable policies (region-specific policies). The results have important policy implications: 1) Strong investment required by the government in the information delivery system (seasonal and weather forecast information). It should incorporate embedding of institutional services, which will gear towards overcoming information and other constraints thus fostering higher adaptation rates related to stress-tolerant breed/species (traits with innate resistance to diseases) and disease control precautions that stabilize production and reduce livestock losses. This will lead to disease recognition and permit prompt response and management, whenever these cases arise because most of the respondents were unaware of local names of these diseases, and have lost their animals even though they have appropriately pursued deworming and seasonal vaccination activity. 2) The positive impact of improved feeding adoption suggests policies that encourage livestock feeding practices among resource-constraint rural poor's, and this can be achieved through formal and informal community groups training. This is vital for information dissemination and for mutual support to help them with needed resources for the implementation of these strategies. 3) In our results, off farm income's association with less adoption suggests a policy intervention that should encourage on-farm diversification through information related to opportunity cost of on-farm improvements and resource allocation. 4) Different adoption practices suggest that institutional services with livestock herders' education should be tailored to motivate them to adopt optimal combinations of strategies and not to rely on a single strategy. 4) New techniques should be developed for the detection, response, and control of infectious diseases because most of the respondents were unaware of disease occurrence, spread, persistence and spillover which resulted in livestock losses. Eliminating the gaps in current knowledge while equipping veterinary personnel with precise statistics of disease presence, dispersal, impacts, and costs for control can lead to better outcomes. Multivalent vaccines or insecticides for multiple diseases (climate-sensitive infectious diseases) should be introduced because it would be cost-effective as well as useful. Restructuring and advancing data collection efforts that results upcoming policies to be science-based. 5) These policies should be updated on the base of ground realities and attention should be given to the resource-poor livestock farmers, whose proportion is more than two-thirds of the total farming population in Pakistan.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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3. 4. Perceptions, vulnerability and adaptation strategies for mitigating climate change effects among small livestock herders in Punjab, Pakistan



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# Perceptions, Vulnerability and Adaptation Strategies for Mitigating Climate Change Effects among Small Livestock Herders in Punjab, Pakistan

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**Abstract:** Pakistan is an agrarian nation that is among the most vulnerable countries to climatic variations. Around 20% of its GDP is produced by agriculture, and livestock-related production contributes more than half of this value. However, few empirical studies have been conducted to determine the vulnerability and knowledge of livestock herders, and particularly the smaller herders. Comprehending individual perceptions of and vulnerabilities to climate change (CC) will enable effective formulation of CC mitigation strategies. This study intended to explore individual perceptions of and vulnerabilities to CC based on a primary dataset of 405 small livestock herders from three agro-ecological zones of Punjab. The results showed that livestock herders' perceptions about temperature and rainfall variations/patterns coincide with the meteorological information of the study locations. The vulnerability indicators show that Dera Ghazi Khan district is more vulnerable than the other two zones because of high exposure and sensitivity to CC, and lower adaptive capacity. However, all zones experience regular livelihood risks due to livestock diseases and deaths resulting from extreme climatic conditions, lower economic status, and constrained institutional and human resource capabilities, thus leading to increased vulnerability. The results indicate that low-cost local approaches are needed, such as provision of improved veterinary services, increased availability of basic equipment, small-scale infrastructure projects, and reinforcement of informal social safety nets. These measures would support cost-effective and sustainable decisions to enable subsistence livestock herders to adopt climate smart practices.

**Keywords:** perception; vulnerability; livestock herders

## 1. Introduction

In the 20th century, climate change (CC) has posed significant challenges for nations and the global community, in addition to posing threats for future generations [1–3]. Climatic variations, in the form of erratic rainfall, intermittent droughts, deadly cyclones, and heat waves, pose threats to all sectors of the economy and walks of life, both marine and land-based [4]. Due to its high dependence on natural resources, such as water, temperature, light, soil, and oxygen, and vulnerability to events that may result from any natural imbalance, the agriculture sector is one of the most sensitive to CC, thus threatening millions of subsistence farmers who heavily rely on the sector's performance [5,6]. In developing countries, the level of vulnerability of small farmers to CC is further intensified because of their low adoptive capacity, poor institutional support, and the temporary nature of resilience-enhancing infrastructure [7,8]. The current risk to households' well-being and food security is higher in these countries because smallholders' livelihoods are more exposed to CC [9–11]. It is expected that CC will affect the occurrence of diseases, increase the severity and frequency of floods and droughts, increase the probability of crop failure, decrease yields, and increase livestock mortality [6,11–13]. Considering the close association between individuals' income and agricultural production [14], the negative impact of CC on livestock may increase the vulnerability of small livestock herders. However, the degree of vulnerability of a location, system, or household is determined by socioeconomic and environmental factors [15].

Understanding the vulnerability of smallholders' livelihood to climatic extremes against the background of broader transformational shifts in social and regional dynamics, in addition to the multidimensional perspective, has almost become a normative priority in recent years [16], although climate-related questions are debatable for a number of reasons. For instance, a relevant question is whether individuals are capable of noticing or monitoring CC. A second question relates to how individuals respond to climate-related (formal or informal) investigations, given the fact that CC is a long-term phenomenon and individuals have only short-term experiences. A third question relates to an individual's ability to detect changes in atmospheric conditions based only on past memories, given atmospheric change is a slow process that can only be detected with meteorological devices [17,18]. Despite these practical issues, previous researchers [19–23] have tried to explain how individuals comprehend and interpret CC.

The main explanation for individuals' poor comprehension, lack of concern, and limited evaluation regarding CC stems from inadequate and scantily available information [17], and a lack of relevant and timely data from relevant authorities. This lack undermines the ability to effectively adapt [18,24]. To identify CC, individuals must know the significance of CC perception and the adoption of mitigation measures. However, perception of CC is a personal assessment [25] that comprises an individual's understanding, which in turn motivates actions with respect to CC incidence and severity [26]. Thus, an individual must perceive CC before responding to it, and this perception needs to be linked with actual CC for effective adaptation measures. However, it is expected that some—if not all—farmers may not be well placed to detect the abrupt changes resulting from environmental variation [27].

Due to the current pace of CC and its associated impacts, nations must consider CC seriously [28]. Various approaches are taken by individuals and societies to safeguard themselves against the effects of the weather. The extant literature has examined the multidimensional perspectives of CC with an emphasis on risk perception, potential barriers, impacts, adoption intentions, and adaptations in different areas [6,11,29–36]. Ahmad and Ma [16] highlight individual perceptions of CC extreme events, and compare these with meteorological data on temperature and rainfall. Hasan and Kumar [17] report that Bangali (Kalapara) rural people's observations of extreme climatic events with regard to CC perceptions are generally consistent with the scientific evidence. There is also ample evidence on the potential role of region-wise vulnerability assessments to assist in developing national strategies for CC adaptation and facilitating the development of the

adaptive capacity of vulnerable communities [8]. To the best of our understanding, few studies have considered CC vulnerability pertaining to Pakistan [1,16,37]. Surprisingly, no study has been performed in Pakistan in the context of region-wise assessment of livestock herders' perceptions and vulnerability to CC, including a comparison to meteorological data. Comprehending individuals' perceptions of CC and vulnerability would be beneficial for the formulation of effective adaptation strategies [5,8,14] that would ultimately help achieve sustained social and economic development among nations and regions [6,11]. Moreover, CC adaptation measures have numerous benefits [11]. Therefore, to expand the adoption and promotion of CC measures, it is important to explore the determinants of adoption.

Against this background, this study aimed to explore the vulnerability of small livestock herders from a multifaceted and multidimensional perspective, with the intention of determining the perceptions of CC of respondents' in three agro-ecological zones of Punjab, Pakistan. The novelty of this study lies in its contribution to a deeper understanding of livestock herders' perceptions about CC indicators, namely, rainfall, temperature, droughts, flood, and livestock diseases, by assessing their consistency with meteorological information. Such an evidence-based comparison is generally rare in the case of Pakistan and other parts of the world. Based on the vulnerability-level outcomes from the three studied zones, the study suggests suitable policy options that may help the public and private sectors to effectively plan for effective mitigation of the harmful effects related to CC.

#### *Vulnerability Assessment*

Vulnerability assessment is a complex and a multidimensional concept. Its level varies across temporal and spatial scales while heavily depending on demographic, socioeconomic, geographic, cultural, institutional, governance and environmental factors [38–41]. It is considered in various dimensions according to its requirements [42,43]. There are numerous approaches and interpretations of vulnerability [41,44–46], although there is little consensus about its definition [47–49]. Brooks et al. [50] define vulnerability as a degree of exposure/risk and incapability to fight climatic variations. Regardless of the different definitions of vulnerability, the most accepted and comprehensive definition provided by the Intergovernmental Panel on Climate Change (IPCC) [51] is: "The degree to which a system, location, or household is susceptible to, or incapable to cope with adverse effects of climate variability and extremes. It is a function of character, magnitude, and rate of climatic deviations to which a system, location, or household is exposed, sensitive, and its adaptive capacity." This interpretation is also typically acknowledged by the academic community [52]. Thus, three elements of vulnerability are consistently considered in the literature: first, exposure to climatic extremes; second, sensitivity to those climatic extremes; and third, the adaptive capacity to cope or recover from climatic extremes [12,40,53].

Considering vulnerability dimensions, exposure is the extent or level to which a system is exposed to major climatic deviations. Sensitivity means the degree to which a system is affected (directly or indirectly) by climatic stimuli, either positively or negatively. Finally, adaptive capacity means the capability of a system to effectively respond to climatic variations, and may involve adjustments in behavior, resources, and technologies [8]. The most extensively-used approach for CC vulnerability assessment is based on the framework suggested by the IPCC. This offers a suitable mechanism to recognize the causes of environmental disaster [54] and proposes appropriate adaptation measures to mitigate its adverse impacts [55,56]. The vulnerability assessment approach can be executed at different scales, such as the household or individual level, community level, regional, or country level [57–59]. However, as noted by Pearson et al. [60], there are numerous concepts and means of assessing vulnerability that occasionally overlap with each other. Nevertheless, the major aim of the vulnerability assessment is to focus the development of appropriate policies that may increase sectors' resilience against CC [50,57,61].

## 2. Materials and Methods

### 2.1. Study Area, Sampling and Data Collection Method

The target population for the current investigation consisted of small livestock herders from three agro-ecological zones (Dera Ghazi Khan (DGK) from the low intensity zone, Rahim Yar Khan (RYK) from the cotton-wheat zone, and Faisalabad (FSD) from the mixed cropping zone) of Punjab province in Pakistan (Figure 1). A multistage sampling strategy was used for data collection. Thirty villages were chosen through a field survey conducted in each agro-ecological zone, and 4–5 households were then randomly selected from each village (Figure 2). In total, field-level primary data were collected from 405 small livestock herders using a pre-tested questionnaire. Responses were verified from key informant interviews before final field observations. The questionnaire was primarily constructed in accordance with the literature [62,63]. A structured questionnaire for data collection was divided into different sections, including general information, household characteristics (socio-economic characteristics), farm characteristics, institutional characteristics, accessibility and availability of resources, assets (livestock and household assets), household income (off/on-farm income), and household perception of climate (risk perception, risk experience, and impacts) to assess exposure to CC, adaptive capacity at the household level, and intentions to adopt practices in response to CC. The indicators used in the current study were primarily based on authors' own understanding of the study location, in addition to peers' knowledge and the published literature [4–6,8,11,16].

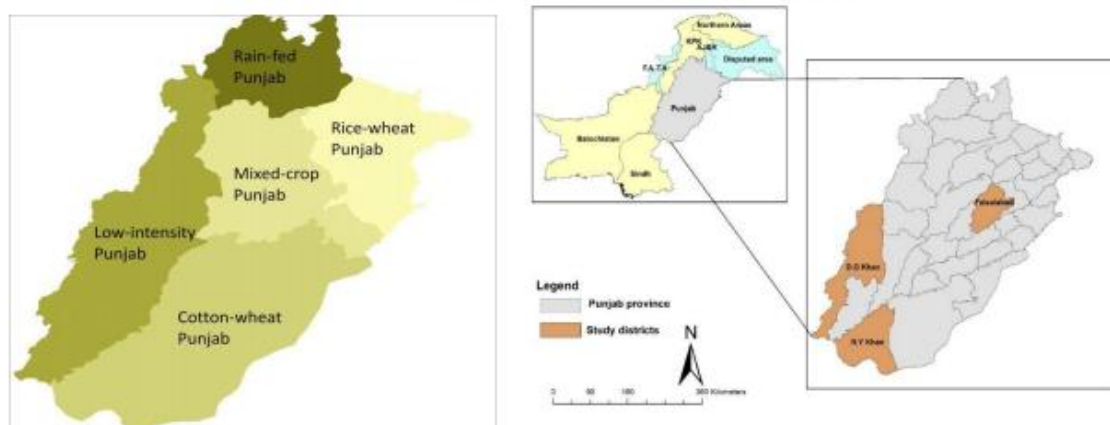


Figure 1. Map categorizing the agro-ecological zones of Punjab and the study area.

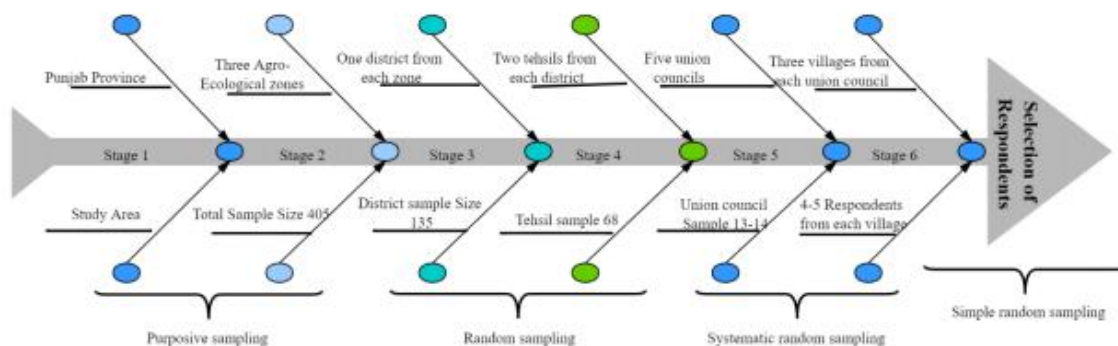


Figure 2. Sampling strategy.

Data collection was undertaken between January and June 2019 by the trained interviewers through face-to-face questioning in the local (*Saraiki* and *Punjabi*) languages. Because the questionnaire language was English, this facilitated the interpretation of the message by the respondents, whose literacy rate was low. On average, interviews took 30–40 min. A confidential protocol was followed related to identification of respondents and the village information, which were confined solely to the serial number of the questionnaire. For the current investigation, meteorological data were obtained from the Punjab province's meteorological department for the period 2010–2019 related to the selected three agro-ecological zones. Quantitative (socio-demographic and economic characteristics, etc.) and qualitative (risk perception of frequency of events/variations over the past 10 years, etc.) data were used to analyze the survey information. Statistical Package for Social Science (SPSS) 24.0 and an MS-Excel work sheet were used for data analysis.

## 2.2. Climate Change Risk Perception Index

In this study, we used the climate change risk perception index (CCRPI) for the calculation of livestock herders' perceptions of climatic events/variations that occurred during the past 10 years but rarely occurred previously [64,65]. A five-point Likert scale was used to collect risk perception data, from the past ten years (2010–2019), of climatic events/variations from 405 respondents. The scale ranges from very low/no perception to very high perception. For the calculation of CCRPI, we assigned a specific value to each perception scale: 4 for very high perception, 3 for high perception, 2 for medium perception, 1 for low perception, and 0 for very low/zero perception. Respondents' evaluations of each climatic event were obtained by interview and recorded as frequencies. The following equation was used to estimate the climate change risk perception score (CCRPS):

$$CCRPS = CCRP_{vh} * 4 + CCRP_h * 3 + CCRP_m * 2 + CCRP_l * 1 + CCRP_{vl/0} * 0$$

where  $CCRP_{vh}$  is the frequency of respondents having very high perception,  $CCRP_h$  is the frequency of respondents having high perception,  $CCRP_m$  is the frequency of respondents having medium perception,  $CCRP_l$  is the frequency of respondents having low perception, and  $CCRP_{vl/0}$  is the frequency of respondents having very low/zero perception. Moreover, CCRPS for any climatic events/variation ranged from lower boundary to higher boundary, i.e., from 0 to 1620, respectively. For further interpretation, we transformed CCRPS into a standardized index. The following equation was used for standardization:

$$\text{Standardized climate change risk perception index (SCCRPI)} = \frac{\text{Total CCRPS}}{\text{Maximum boundary value}}$$

The SCCRPI values ranged from 0 (minimum level of risk perceived by livestock herders) to 100 (maximum level of risk perceived). We then ranked this score.

## 2.3. Vulnerability Index

For the estimation of vulnerability, the IPCC framework was used [38]. This study adopted the index-based method used by Dendir and Simane [4] to calculate small livestock herders' vulnerability levels. By the following vulnerability assessment module, relevant indicators were calculated from major and sub-components of a specific dimension/domain. Each major component included varying numbers of sub-components. All the indicators were normalized using a balanced weighted average approach, thus assuming that all indicators contributed equally to the overall index according to the functional relationship with vulnerability [4,14]. To standardize the indicators, Equation (1) was used as:

$$index_{xv} = \frac{X_v - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where  $X_{min}$ ,  $X_{max}$ , and  $X_v$  are, respectively, the minimum, maximum, and actual value of specific indicator for a particular household, across all households [5]. For the calculation

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$$index_{iv} = \frac{X_v - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where  $X_{min}$ ,  $X_{max}$ , and  $X_v$  are, respectively, the minimum, maximum, and actual value of specific indicator for a particular household, across all households [5]. For the calculation

of each major component value, each indicator of sub-components was standardized and then averaged using Equation (2):

$$M_v = \frac{\sum_{i=1}^n IndexX_{vi}}{n} \quad (2)$$

where  $M_v$  denotes one of the 11 major components of the vulnerability, namely, extreme events, climatic variables, food and health, land and livestock, livelihood, belonging to the vulnerable group, adaptation efficacy, self-efficacy, economic capability, human resource capability, and institutional capability; the sub-components are represented by the index, where the index is denoted by  $i$  and  $n$  denotes the number of sub-components for each major component. Once values for each of the 11 major components for three agro-ecological zones were calculated, they were then averaged using Equation (3):

$$LVI_v = \frac{\sum_{i=1}^{11} W_{mi} M_{vi}}{\sum_{i=1}^{11} W_{mi}} \quad (3)$$

where  $W_{mi}$  is the weight of each major component. The LVI is scaled from 0 (least vulnerable) to 0.7 (most vulnerable). Because the IPCC framework was used for the estimation of the contributing factors (exposure, sensitivity, and adoptive capacity) of vulnerability [66], we placed exposure under extreme events and climatic variables. Sensitivity is defined as the food and health, land and livestock, livelihood, and belonging to the vulnerable group. Adoptive capacity is defined as adaptation efficacy, self-efficacy, economic capability, human resource capability, and institutional capability. For climatic variables, respondents' perceptions of climate change during the past ten years (2010–2019) and Pakistan meteorological data (PMD) were used in the form of the mean and standard deviation of monthly average minimum temperature, mean and standard deviation of monthly average maximum temperature, and mean and standard deviation of monthly average rainfall. Equations (1) and (3) were used to estimate  $LVI_{IPCC_v}$  whereas Equation (4) was used to calculate the vulnerability contributing factors toward  $LVI_{IPCC_v}$ :

$$CF_v = \frac{\sum_{i=1}^{11} W_{mi} M_{vi}}{\sum_{i=1}^{11} W_{mi}} \quad (4)$$

where  $CF_v$  represents vulnerability contributing factors (exposure, sensitivity, and adoptive capacity) among the three agro-ecological zones.  $M_{vi}$  denotes the major components for each zone indexed by  $i$ , and  $n$  is the number of major components in  $CF_v$ .  $LVI_{IPCC_v}$  is calculated using Equation (5):

$$LVI_{IPCC_v} = (CF_{ed} - CF_{ad}) * CF_{sd} \quad (5)$$

where  $CF_{ed}$ ,  $CF_{sd}$ , and  $CF_{ad}$  represent factors contributing to exposure, sensitivity, and adoptive capacity for each zone, respectively.  $LVI_{IPCC_v}$  ranges from  $-1$  to  $+1$  for least-vulnerable to most-vulnerable, respectively.

#### 2.4. Drivers of Adoption

We analyzed drivers of adoption of climate change strategies among the sampled livestock farmers based on the information gathered about the nature of adaptation measures being followed by the farmers. Numerous local adaptation strategies were being adopted by the livestock herders. Here, we categorized four major adaptations: (1) improve feeding (diet supplements, grazing management, practicing concentrate, and bran feeding); (2) provision of medical facilities (disease control precaution, involvement in livestock training); (3) updating with seasonal and weather forecast information; and (4) livestock diversification and improved/stress-tolerant breed/species. The values of respondents adopting these strategies were 57.3%, 23.5%, 28.6%, and 16.8%, respectively. Each adaptation received a separate response relative to livestock herders' socioeconomic

characteristics. Therefore, we used a binary logit model to analyze the relationship between livestock herders' adaptations and their socio-economic characteristics. These adaptations were considered to be a dependent variable and their values were recorded as 1 (if adopted) and 0 (otherwise). The following model was used for analysis:

$$Y_i = \beta_0 + \beta_i X_i + \varepsilon_i$$

where  $Y_i$  = dependent variables (adaptation strategies adopted by livestock herders),  $\beta_0$  = constant,  $\beta_i$  = coefficient of independent variables,  $X_i$  = explanatory variables, and  $\varepsilon_i$  represents the error term. The explanatory variables used in the present research were age, experience, family size, education, household type, area under fodder, farm assets, basic repair facilities in the village, off-farm income, and distance from market. Numerous studies have focused on drivers in different dimensions [11,67–69]. We included these variables in our study due to their anticipated impact on adaptations in numerous adoption studies [11,70,71]. Table 1 shows the anticipated signs of independent variables that were used in the study.

**Table 1.** Description of model variables.

| Explanatory Variables              | Expected Sign | Reference     |
|------------------------------------|---------------|---------------|
| Age (years)                        | −, +          | [71,72]       |
| Experience (Years)                 | +             | [63,70,73–75] |
| Family Size (Years)                | +             | [34,76]       |
| Education                          | +             | [74,75,77,78] |
| Household type                     | +             | [11,34,76]    |
| Area under fodder (Acre)           | −, +          | [11,34,70]    |
| Farm Assets (number)               | +             | [79]          |
| Cooking fuel                       | −, +          | [80]          |
| Basic repair facilities in village | +             | [70]          |
| Off-farm income                    | −, +          | [70,74]       |
| Distance to market (km)            | −, +          | [70]          |

### 3. Results

#### 3.1. Socio-Demographic Characteristics of Study Participants

Table 2 presents selected socio-demographic characteristics of the respondent livestock herders. The average age of the respondents in DGK, RYK, and FSD was 45.75, 43.61, and 43.83 years, respectively, representing middle-aged respondents. The frequency distribution of respondents' education level showed that the majority of the respondents belonging to DGK and RYK were illiterate (53 and 42 percent, respectively) or had primary-level education (51 and 59, respectively), and had an education degree below college level. By comparison, in FSD, the education level was higher relative to the other two zones. In terms of livestock rearing experience, nearly half of the livestock herders from the three zones had more than 20 years' experience, with average experience of 21.52, 23.32, and 21.30 years, respectively. The family size was large in all zones, i.e., around 12, 10, and 7 persons per household, respectively, of which with majority of family members were middle-aged (16–65 years).

To assess vulnerability in the context of the identification of threats from CC, resilience must also be considered in relation to the socio-economic status of the respondents, household characteristics, off farm income, and basic institutional facilities. Respondents were asked about their type of lavatory in reference to their living standard. The majority of livestock herders had flush-type lavatory systems in their homes. The results also revealed that the majority of the respondents in DGK and RYK used wood for fuel with constrained household amenities. In contrast, an opposite trend was evident in FSD where respondents used Liquefied Petroleum Gas (LPG) for cooking purposes with supplemented livelihood amenities. Given the nature of the study, and because the sampled households were involved in livestock rearing, the area under fodder of the majority of the respondents was

approximately equal to or less than 2 acres. The majority of the livestock herders of the three zones had to travel up to 20 km to reach different markets to sell their produce or purchase household and farm-related goods/inputs.

**Table 2.** Socio-demographic and economic characteristics of study participants.

| Characteristics                                  | Group            | Agro-Ecological Zones (Study Area) |       |      |
|--------------------------------------------------|------------------|------------------------------------|-------|------|
|                                                  |                  | DGK                                | RYK   | FSD  |
| Age (years)                                      | ≤30              | 11                                 | 17    | 17   |
|                                                  | 31–50            | 82                                 | 89    | 86   |
|                                                  | ≥50              | 42                                 | 29    | 32   |
| Experience (Years)                               | ≤20              | 63                                 | 61    | 74   |
|                                                  | 21–35            | 65                                 | 56    | 52   |
|                                                  | ≥36              | 7                                  | 18    | 9    |
| Age-wise Avg. Number of Family Members (Years) * | ≤15              | 4.71                               | 3.96  | 2.44 |
|                                                  | 15 ≤ age ≤ 65    | 7.03                               | 6.04  | 4.56 |
|                                                  | ≥65              | 0.41                               | 0.26  | 0.42 |
|                                                  | Total            | 12.15                              | 10.26 | 7.42 |
| Education                                        | Illiterate       | 53                                 | 42    | 21   |
|                                                  | Primary          | 51                                 | 59    | 19   |
|                                                  | High school      | 23                                 | 29    | 55   |
|                                                  | College/above    | 8                                  | 5     | 40   |
| Household type                                   | Nuclear          | 60                                 | 57    | 33   |
|                                                  | Joint            | 75                                 | 78    | 102  |
| Area under fodder (Acre)                         | ≤2 acre          | 109                                | 130   | 117  |
|                                                  | ≥2.1 acre        | 26                                 | 5     | 18   |
| Farm Assets (number)                             | Zero asset       | 38                                 | 55    | 42   |
|                                                  | 1–2              | 72                                 | 58    | 48   |
|                                                  | 3–4              | 25                                 | 22    | 45   |
| Cooking fuel                                     | Wood             | 126                                | 98    | 35   |
|                                                  | LPG (and others) | 9                                  | 37    | 100  |
| Basic repair facilities in village               | No               | 95                                 | 92    | 31   |
|                                                  | Yes              | 40                                 | 43    | 104  |
| Off-farm income                                  | No               | 62                                 | 27    | 64   |
|                                                  | Yes              | 73                                 | 108   | 71   |
| Distance to market (km)                          | ≤10              | 48                                 | 64    | 8    |
|                                                  | 11–20            | 70                                 | 46    | 70   |
|                                                  | ≥21              | 17                                 | 25    | 57   |

Source: Field survey. Note: All the variables in this table report frequencies, with the exception of family size, which is represented by the average number of family members in various age categories. \* This information is based on the average number of family members per household for the three age-groups, i.e., ≤15 years, 15–65 years, and above 65 years of age. Summing the mean number of family members in each age-category yields the average household size for respective agro-ecological zone.

In the study area, respondents were also inquired about their assets for supporting their livelihood and farming operations. Here, we only considered agricultural equipment such as tractors, trolleys, tube-wells, and threshers to gain insights into respondents' economic condition. The results in Table 2 show that the majority of the respondents owned only one or two pieces of equipment from the four machines listed above, with most having their own tube-well for irrigation purposes. The survey's results also show that a minority of farmers had their own tractor due to poor economic conditions. However, it was previously established that ownership of agricultural assets stimulates agriculture growth and reduces poverty levels [1,75,81]. The majority of the respondents of the three zones were involved in off-farm activities for livelihood diversification. Having off-farm income sources is considered to be an adaptation measure against various risk sources, including CC, while also fostering adaptive capacity [6,74]. In addition, at the individual and household levels, larger capital endowments rapidly help to mitigate risks associated

with climatic extremes. However, in developing countries such as Pakistan, smallholders remain at risk of climatic extremes due to having a poor resource base [31].

### 3.2. Livestock Herders' Climate Change Perceptions and Meteorological Data

Study participants were asked questions regarding their concerns and perceptions about the frequency and intensity of CC events they had observed in the past 10 years. We only considered responses narrated by the majority of respondents who believed that CC was occurring in terms of climate-related events that had not previously occurred. Table 3 lists these perceptions of the respondents in the study area. It is clear that, in the past 10 years, the majority of the respondents observed an increase in high and low temperature variations. They also believed that the rainfall pattern had changed while noting a drop in the frequency of extreme climatic events (droughts and floods), and thus considered these events to be less threatening. As noted earlier, the majority of the respondents (174, 142, and 122) mentioned that the frequency of high/low temperature and rainfall intensity was high, whereas the remainder of the responses indicated the frequency was in the range of medium to very high. Respondents also observed abrupt changes in summer and winter temperatures, as being higher and lower, respectively, compared with the past. These findings agree with those of Abid et al. [37] and Ahmad and Ma [16] in the case of Punjab province. Additionally, livestock herders believed that CC led to the emergence of new diseases among their animals with an increased frequency and intensity, and indicated a frequency in the range of high/very high.

**Table 3.** Responses of CC risk perception events/variations during the past 10 years that rarely occurred previously.

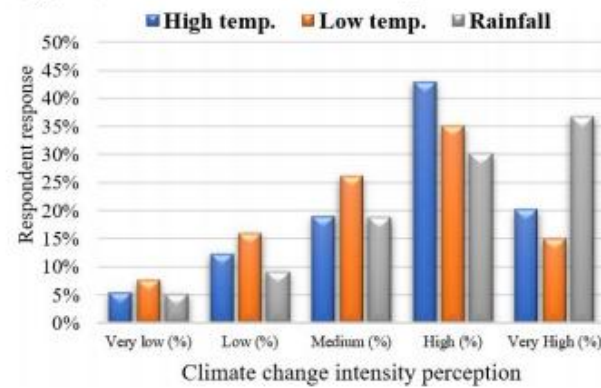
| Climate Change Events   | Frequency |     |        |      |           | CCRPS | SCCRPI | Rank |
|-------------------------|-----------|-----|--------|------|-----------|-------|--------|------|
|                         | Very Low  | Low | Medium | High | Very High |       |        |      |
| Drought                 | 184       | 95  | 67     | 29   | 30        | 436   | 26.914 | 6    |
| High temperature        | 22        | 50  | 77     | 174  | 82        | 1054  | 65.062 | 3    |
| Low temperature         | 31        | 65  | 106    | 142  | 61        | 947   | 58.457 | 4    |
| Animal diseases         | 27        | 47  | 81     | 116  | 134       | 1093  | 67.469 | 2    |
| Rainfall Pattern Change | 21        | 37  | 76     | 122  | 149       | 1151  | 71.049 | 1    |
| Flood                   | 186       | 96  | 47     | 55   | 21        | 439   | 27.099 | 5    |

Source: Field survey.

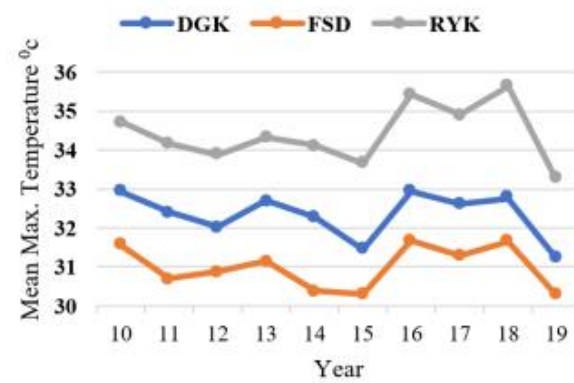
However, the measurement of climate change risk perception depends on demographic, social, economic, and cultural characteristics [70]. The perception of risk is a mental construct and personal perception may vary among individuals [82]. The literature provides numerous evidence of perceptions calculated using the Likert scale [64,65]. In the present research, we used the Likert scale to assess livestock herders' risk perceptions regarding climate change. Table 3 shows the responses of CC risk perception events/variations over the past 10 years and the calculated values of CCRPS and SCCRPI. CCRPS values ranged from 436 to 1151 and SCCRPI values ranged from 26.914 to 71.049. The values showed that livestock herders ranked drought at the lowest level and rainfall pattern change at the highest level of risk perceived from climate change.

The responses relating to respondents' perceptions about temperature (high temperature, low temperature) and rainfall pattern are shown in Figure 3. Similarly, livestock herders' perceptions about the above-mentioned CC indicators are compared with the past 10 years' (2010–2019) meteorological data for the study area. Results showed that respondents' perceptions of the trends in high and low temperatures were verified by the annual mean plotted trends, as shown in Figures 4 and 5, respectively. The graphs show that perceptions about temperature (high/low) were consistent with the meteorological data. The fluctuating trend in temperature is consistent with the stated perceptions of the respondents, both for summers and winters in the study locations. In the case of rainfall, the majority of respondents perceived that the pattern had also changed. The meteorologi-

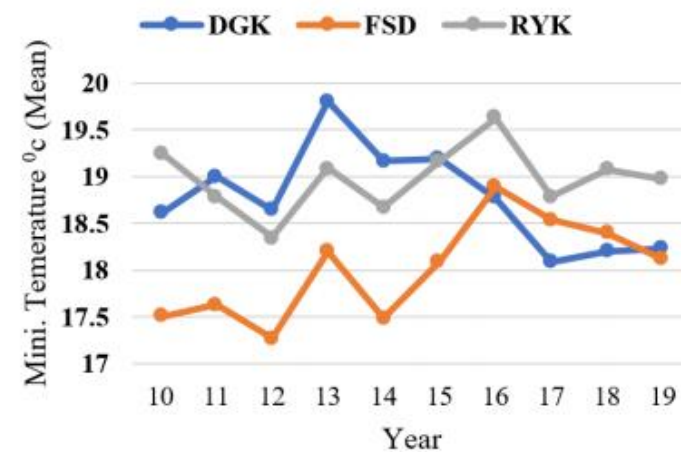
cal data on annual rainfall show a fluctuating trend each year during the period 2010–2019 (Figure 6), and are consistent with the respondents' observations.



**Figure 3.** Respondents' stated perceptions about high/low temperature and rainfall during the past 10 years.



**Figure 4.** Maximum temperature (mean) of study locations (2010–2019).



**Figure 5.** Minimum temperature (mean) of study locations (2010–2019).

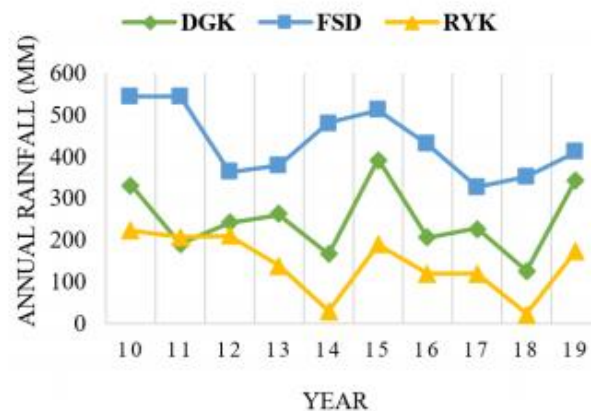


Figure 6. Annual rainfall in the study locations (2010–2019).

The specific climate-related characteristics of the selected agro-ecological zones for the period 2010–2019 were derived from the processing of meteorological data. The results show that, from 2010 to 2019, the annual minimum/maximum temperature (mean) of DGK, RYK, and FSD were 18.77/32.34, 18.98/34.41, and 18.01/30.99, respectively. The annual rainfall from 2010 to 2019 of DGK, RYK, and FSD was 248.98, 143.43, and 434 mm, respectively. Consequently, these zones were characterized by a mean annual temperature in the range of around 18.6–32.6 °C, and total annual rainfall in the range of 143 to 434 mm, during the study period.

### 3.3. Contributing Factors of Vulnerability

#### 3.3.1. Exposure Assessment

Exposure is considered to be a major dimension of vulnerability, and refers to changes in key variables of the climatic system (e.g., precipitation and temperature) and extreme events (drought, flood, and animal diseases). In the present research, the exposure assessment was based on respondents' perceptions and was compared with the regional climatic data (rainfall, minimum temperature, maximum temperature) provided by the Pakistan meteorological department (PMD). Within exposure, two major components were categorized into nine sub-components (Table 4): extreme events (defined as past 10 years' experienced animal diseases, drought, and flood intensity), and climatic variables (defined as past 10 years' observed min/max temperature variation, rainfall and region-wise PMD data of annual mean min/max temperature and rainfall).

Table 4. Vulnerability indicators (major components and sub-components) and functional relationship with vulnerability.

| Contributing Factor | Major Components   | Sub Components (Indicators)                                                                    | Description                                                                                   | Relationship ** |
|---------------------|--------------------|------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|-----------------|
| Exposure            | Extreme Events     | Past 10 years observed drought intensity                                                       | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     |                    | Past 10 years observed flood intensity                                                         | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     |                    | Past 10 years observed animal diseases                                                         | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     |                    | Past 10 years observed high temperature variation                                              | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     |                    | Past 10 years observed low temperature variation                                               | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     | Climatic Variables | Past 10 years observed rainfall variation                                                      | Measured in a 5 point scale 1 (very low) to 5 (very high)                                     | +               |
|                     |                    | Annual mean minimum temperature °C (2010–2019) PMD *                                           | Mean standard deviation of monthly average minimum temperature                                | +               |
|                     |                    | Annual mean maximum temperature °C (2010–2019) PMD *                                           | Mean standard deviation of monthly average maximum temperature                                | +               |
|                     |                    | Annual mean rainfall (2010–2019) PMD *                                                         | Mean standard deviation of monthly average rainfall                                           | +               |
|                     |                    | Increase in the depth of subsoil water (past 10 years observation)                             | Per centage                                                                                   | +               |
| Sensitivity         | Food and Health    | Dairy yields/milk production/ family (past 10 years trend)                                     | Measured in a 3 point scale (1) no change (2) decrease (3) increase                           | +               |
|                     |                    | Milk in diet (respondent past 10 years consumption trend)                                      | Measured in a 3 point scale (1) no change (2) decrease (3) increase                           | +               |
|                     |                    | Meat in diet (respondent past 10 years consumption trend)                                      | Measured in a 3 point scale (1) no change (2) decrease (3) increase                           | +               |
|                     |                    | Child growth performance (respondent past 10 years observation)                                | Measured in a 3 point scale (1) no change (2) decrease (3) increase                           | +               |
|                     |                    | Amount of food consumed was below than desired quantity (respondent past 10 years observation) | Measured in a 3 point scale (1) No (2) yes for a couple a day's (3) yes for a couple of weeks | +               |
|                     | Land and Livestock | Average land of household members (acres)                                                      | Own land/total number of family members                                                       | -               |
|                     |                    | Number of livestock losses in past 10 years (count)                                            | Number                                                                                        | +               |
|                     |                    | Have you experienced fodder shortages in past 10 years?                                        | (1) Yes (2) otherwise                                                                         | +               |
|                     |                    | Change in total number of livestock during past 10 years                                       | Measured in a 3 point scale (1) no change (2) decrease (3) increase                           | +               |
|                     |                    | Take out children from school in past 10 years                                                 | (1) Yes (2) otherwise                                                                         | +               |
| Vulnerable Group    | Livelihood         | Have you changed the employment or work pattern in past 10 years                               | (1) Yes (2) otherwise                                                                         | +               |
|                     |                    | Applied for extended term of loan due to climate disaster in past 10 years                     | (1) Yes (2) otherwise                                                                         | +               |
|                     | Household          | Household members less than 15 years (count)                                                   | Number                                                                                        | +               |
|                     |                    | Household members greater than 65 years (count)                                                | Number                                                                                        | +               |

Table 4. Cont.

| Contributing Factor | Major Components          | Sub-Components (Indicators)                                                                  | Description                                                             | Relationship ** |
|---------------------|---------------------------|----------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|-----------------|
| Adaptive Capacity   | Adaptation Efficacy       | I am very positive about climate change adoption measures                                    | Measured in a 5-point scale 1 (strongly disagree) to 5 (strongly agree) | -               |
|                     | Self-Efficacy             | I plan to adopt measures for climate change                                                  | Measured in a 5-point scale 1 (strongly disagree) to 5 (strongly agree) | -               |
|                     |                           | It is mostly up to me, whether or not to adopt climate change measures for my livestock      | Measured in a 5-point scale 1 (strongly disagree) to 5 (strongly agree) | ±               |
|                     | Economic Capability       | Have adequate ability (knowledge and skills) to implement climate change measures on my farm | Measured in a 5-point scale 1 (strongly disagree) to 5 (strongly agree) | -               |
|                     |                           | Financial and structural barrier prohibit me to adopt climate change measures                | Measured in a 5-point scale 1 (strongly disagree) to 5 (strongly agree) | +               |
|                     | Human Resource Capability | Total number of livestock (count)                                                            | Number                                                                  | -               |
|                     |                           | Adult family members (count)                                                                 | Number                                                                  | -               |
|                     |                           | Household head education (years)                                                             | Years                                                                   | -               |
|                     | Institutional Capability  | Livestock experience (years)                                                                 | Years                                                                   | +               |
|                     |                           | Distance to reach the road (km)                                                              | Km                                                                      | +               |
|                     |                           | Distance to market (km)                                                                      | Km                                                                      | +               |
|                     |                           | Basic repair facilities available in village                                                 | (1) Yes (0) otherwise                                                   | -               |

\* Pakistan meteorological department; \*\* Relationship between vulnerability and indicator: (+) represents positive relationship between vulnerability and indicator, and (−) represents negative.

The analysis showed that livestock herders from DGK were more exposed to extreme events and more vulnerable to drought (0.535), flood (0.543), and animal diseases (0.774) compared with those in RYK and FSD, who had relatively milder exposure to drought (0.141, 0.131), flood (0.128, 0.285), and animal diseases (0.561, 0.689), respectively. The average scores of the extreme events were 0.617, 0.227, and 0.369 for DGK, RYK, and FSD, respectively, signifying a greater exposure of DGK's livestock herders to extreme events than those in the other two zones. Similarly, district-wise average scores of climatic variables were 0.584, 0.548, and 0.607 for DGK, RYK, and FSD, respectively, implying a greater exposure of FSD to climatic stimuli than the other two zones (Table 5).

Table 5. Indexed sub-components and overall livelihood vulnerability index (LVI).

| Major-Components                               | Code  | Sub-Components                                                                                 | Agro-Ecological Zones |        |        |
|------------------------------------------------|-------|------------------------------------------------------------------------------------------------|-----------------------|--------|--------|
|                                                |       |                                                                                                | DGK                   | RYK    | FSD    |
| Extreme Events                                 | EXP1  | Past 10 years observed drought intensity                                                       | 0.535                 | 0.141  | 0.131  |
|                                                | EXP2  | Past 10 years observed flood intensity                                                         | 0.543                 | 0.128  | 0.285  |
|                                                | EXP3  | Past 10 years observed animal diseases                                                         | 0.774                 | 0.561  | 0.689  |
| Climatic Variables                             |       |                                                                                                | 0.617                 | 0.227  | 0.369  |
|                                                | EXP4  | Past 10 years observed high temperature variation                                              | 0.576                 | 0.526  | 0.608  |
|                                                | EXP5  | Past 10 years observed low temperature variation                                               | 0.596                 | 0.472  | 0.607  |
|                                                | EXP6  | Past 10 years observed rainfall variation                                                      | 0.796                 | 0.578  | 0.738  |
|                                                | EXP7  | Annually mean standard deviation of minimum temperature (2010–2019) PMD *                      | 0.536                 | 0.382  | 0.526  |
|                                                | EXP8  | Annually mean standard deviation of maximum temperature (2010–2019) PMD *                      | 0.599                 | 0.762  | 0.557  |
|                                                | EXP9  | Annual rainfall (2010–2019) PMD *                                                              | 0.461                 | 0.600  | 0.490  |
|                                                |       |                                                                                                | 0.584                 | 0.548  | 0.607  |
| Food and Health                                | SEN1  | Increase in the depth of subsoil water (past 10 years observation)                             | 0.403                 | 0.410  | 0.293  |
|                                                | SEN2  | Dairy yields/milk production/farm (past 10 years trend)                                        | 0.561                 | 0.456  | 0.670  |
|                                                | SEN3  | Milk in diet (respondent past 10 years consumption trend)                                      | 0.561                 | 0.441  | 0.452  |
|                                                | SEN4  | Meat in diet (respondent past 10 years consumption trend)                                      | 0.565                 | 0.441  | 0.433  |
|                                                | SEN5  | Child growth performance (respondent past 10 years observation)                                | 0.407                 | 0.370  | 0.415  |
|                                                | SEN6  | Amount of food consumed was below than desired quantity (respondent past 10 years observation) | 0.481                 | 0.481  | 0.526  |
| Land and Livestock                             |       |                                                                                                | 0.503                 | 0.433  | 0.432  |
|                                                | SEN7  | Average land of household members                                                              | 0.078                 | 0.150  | 0.160  |
|                                                | SEN8  | Number of livestock losses in past 10 years                                                    | 0.201                 | 0.256  | 0.263  |
|                                                | SEN9  | Have you experienced fodder shortage in past 10 years?                                         | 0.581                 | 0.607  | 0.415  |
|                                                | SEN10 | Change in total number of livestock past 10 years                                              | 0.546                 | 0.289  | 0.485  |
| Livelihood                                     |       |                                                                                                | 0.534                 | 0.350  | 0.356  |
|                                                | SEN11 | Took out children from school in past 10 years                                                 | 0.330                 | 0.406  | 0.207  |
|                                                | SEN12 | Have you changed the employment or work pattern in past 10 years                               | 0.539                 | 0.519  | 0.244  |
|                                                | SEN13 | Applied for extended term of loan due to climate disaster in past 10 years                     | 0.195                 | 0.452  | 0.170  |
| Vulnerable Group                               |       |                                                                                                | 0.560                 | 0.489  | 0.207  |
|                                                | SEN14 | Household members less than 15 years                                                           | 0.126                 | 0.330  | 0.144  |
|                                                | SEN15 | Household members greater than 65 years                                                        | 0.136                 | 0.130  | 0.141  |
|                                                |       |                                                                                                | 0.135                 | 0.230  | 0.142  |
| Adaptation Efficacy                            | AC1   | I am very positive about climate change adoption measures                                      | 0.591                 | 0.594  | 0.541  |
|                                                | AC2   | I plan to adopt measures for climate change                                                    | 0.528                 | 0.454  | 0.419  |
| Self-Efficacy                                  |       |                                                                                                | 0.539                 | 0.524  | 0.480  |
|                                                | AC3   | It is mostly up to me, whether or not to adopt climate change measures for my livestock        | 0.405                 | 0.685  | 0.596  |
|                                                | AC4   | Have adequate ability (knowledge and skills) to implement climate change measures on my farm   | 0.420                 | 0.507  | 0.481  |
|                                                |       |                                                                                                | 0.436                 | 0.621  | 0.539  |
| Economic Capability                            | AC5   | Financial and structural barrier prohibit me to adopt climate change measures                  | 0.520                 | 0.591  | 0.619  |
|                                                | AC6   | Total number of livestock                                                                      | 0.247                 | 0.190  | 0.071  |
| Human Resource Capability                      |       |                                                                                                | 0.398                 | 0.391  | 0.345  |
|                                                | AC7   | Adult family members                                                                           | 0.146                 | 0.311  | 0.414  |
|                                                | AC8   | Household head education                                                                       | 0.296                 | 0.281  | 0.565  |
|                                                | AC9   | Livestock experience                                                                           | 0.405                 | 0.351  | 0.446  |
| Institutional Capability                       |       |                                                                                                | 0.302                 | 0.314  | 0.475  |
|                                                | AC10  | Distance to reach the road                                                                     | 0.251                 | 0.257  | 0.233  |
|                                                | AC11  | Distance to market                                                                             | 0.304                 | 0.378  | 0.428  |
|                                                | AC12  | Basic repair facilities available in village                                                   | 0.286                 | 0.319  | 0.770  |
| Overall livelihood vulnerability index (LVI) * |       |                                                                                                | 0.277                 | 0.351  | 0.477  |
|                                                |       |                                                                                                | 0.4309                | 0.4198 | 0.4237 |

\* Note: LVI scale → 0 (least vulnerable) to 0.7 (most vulnerable).

### 3.3.2. Sensitivity Assessment

In the assessment of vulnerability, sensitivity to CC was estimated on the basis of four major components: food and health, land and livestock, livelihood, and belonging to the vulnerable group. These four major components were further sub-divided into several sub-components, as reported in Table 4. The major components of food and health were measured by the response to six sub-components defined as the past ten years' observation/trend/consumption, such as the depth of subsoil water, dairy yields and/or milk production per family, milk in diet, meat in diet, child growth performance, and amount of food consumed. The land and livestock component was accounted for by the average landholding per household, past ten years' livestock losses, fodder shortage, and change in the quantity of livestock. The livelihood component questioned whether, in the past ten years, respondents removed their children from school, changed their employment/work pattern, or applied for an extended loan term due to climatic disaster(s). The vulnerable group was defined as family members who were below 15 or above 65 years of age. The results in Table 5 indicate that respondents were more sensitive to food and health (0.503) in DGK, land and livestock (0.356) in FSD, and livelihood and the vulnerable group (0.489, 230, respectively) in RYK. The overall score of the sensitivity index indicates that RYK was more sensitive (0.395) in comparison with DGK and FSD (0.375 and 0.328, respectively) (see Table 5).

### 3.3.3. Adaptive Capacity Assessment

Adaptive capacity assessment was undertaken on the basis of following major components: adaptation efficacy, self-efficacy, economic capability, human resource capability, and institutional capability, as illustrated in Table 4. Adaptation and self-efficacy were measured on a five-point scale—1 (strongly disagree) to 5 (strongly agree). Economic capability assessed respondents' financial and structural barriers and total number of livestock. Human resource capability was assessed by taking into account the household head's education, livestock rearing experience, and adult family members (number). Institutional capability was assessed on the basis of the distance of the household's residence from main/link road and market, and availability of basic facilities in the village. The scores of adaptation efficacy (0.559, 0.524, and 0.480), self-efficacy (0.456, 0.621, and 0.539), economic capability (0.384, 0.391, and 0.345), human resource capability (0.302, 0.314, and 0.475), and institutional capability (0.277, 0.351, and 0.477), estimated for DGK, RYK, and FSD, respectively, show a mixed picture. The overall district-level scores of the adaptive capacity index for DGK, RYK, and FSD zones, respectively, were 0.375, 0.422, and 0.465, reflecting a low level of adaptive capacity for DGK and RYK to cope with CC (Table 5). Therefore, southern Punjab (DGK, RYK) livestock herders had low adaptive capacity due to a low level of education, less-developed infrastructure, and poor household facilities, as noted during the field survey.

### 3.4. Vulnerability Index Assessment

Based on the findings related to the contributing factors of vulnerability, DGK was the most-vulnerable of the three districts, followed by FSD and RYK. The spider diagram of vulnerability in Figure 7 represents the LVI values encompassing all 11 major components calculated from 36 sub-components (see Table 5 for sub-component results). LVI is scaled from 0 (least vulnerable) to 0.7 (most vulnerable). All sub-component index values and LVI outcomes based on the former are shown in Table 5. Overall, LVI outcomes indicate that DGK (LVI = 0.4309) was more vulnerable than FSD (LVI = 0.4237) and RYK (LVI = 0.4198). DGK was more vulnerable in terms of extreme events (0.617), food and health (0.503), self-efficacy (0.456), human resource capability (0.302), and institutional capability (0.277); FSD was more vulnerable in terms of climatic variables (0.607), land and livestock (0.356), and economic capability (0.345); and RYK was more vulnerable in terms of livelihood (0.489) and the vulnerable group category (0.230) (Table 5 and Figure 7).

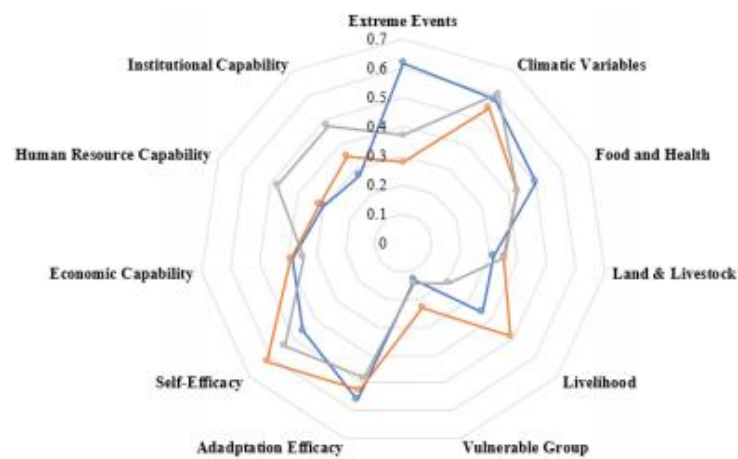


Figure 7. Spider diagram of vulnerability based on major components of LVI of the study area.

The LVI-IPCC scale ranged from  $-1$  (less-vulnerable) to  $1$  (most-vulnerable). Small livestock herders in the DGK were vulnerable to CC in terms of exposure ( $0.595$ ) with lower adaptive capacity ( $0.378$ ). Moreover, respondents in FSD were also vulnerable although less exposed ( $0.528$ ), having lower sensitivity to CC ( $0.328$ ) and a higher level of adaptive capacity ( $0.465$ ) compared with DGK. The farmers in RYK were the least vulnerable, despite being more sensitive ( $0.395$ ) to CC with a lower level of exposure ( $0.458$ ) and a higher level of adaptive capacity ( $0.422$ ) compared with the other two districts (Table 6 and Figure 8).

Table 6. Table LVI-IPCC contributing factors of three agro-ecological zones.

| Contributing Factors | DGK   | RYK   | FSD   |
|----------------------|-------|-------|-------|
| Exposure             | 0.595 | 0.458 | 0.528 |
| Sensitivity          | 0.375 | 0.395 | 0.328 |
| Adaptive capacity    | 0.378 | 0.422 | 0.465 |
| LVI-IPCC *           | 0.081 | 0.014 | 0.020 |

\* LVI-IPCC scale =  $-1$  (less vulnerable) to  $1$  (most vulnerable).

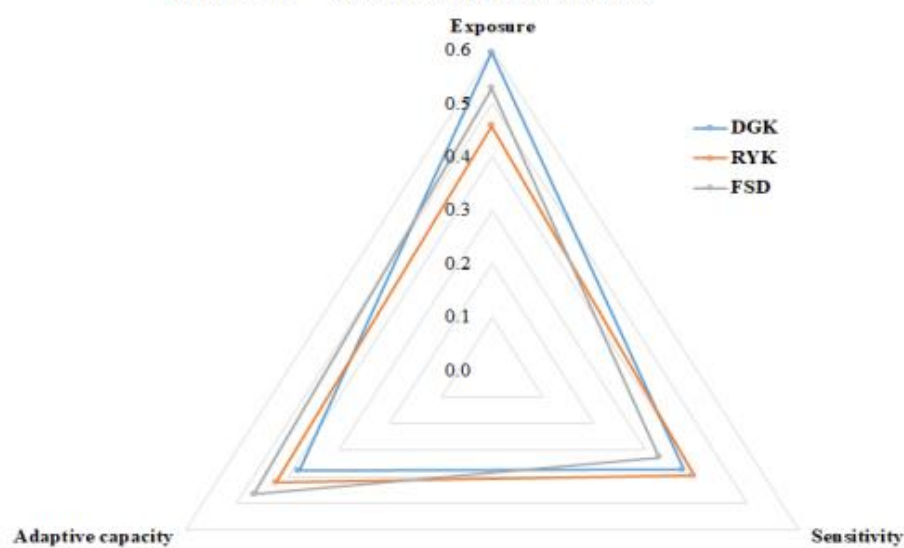


Figure 8. LVI-IPCC contributing factors of the three agro-ecological zones.

In total, DGK was the most vulnerable district of the three (Table 6). The results imply that the high vulnerability level in DGK is attributable to lower adaptive capacity, higher sensitivity, and higher exposure to CC. The higher vulnerability in DGK is due to different factors, such as the farmers' increased dependency on livestock and widespread poverty in the region [16]. Nonetheless, the increase in the frequency and intensity of floods, droughts, and the incidence of new diseases among livestock have marred livestock production. As a result, farmers are more vulnerable with respect to food, health, and livelihood sustenance. The other reasons for increased vulnerability are subsistence livelihood options, such as small farm sizes, poor self-efficacy, and low economic capability, leading to decreased livestock production and lower farm revenues [70]. Moreover, the least involvement in off-farm income generation activities in this zone, compared with the RYK and FSD zones, further intensify the region's vulnerability to CC. Human resource capability and institutional capability in DGK were also lower compared to those of the other zones. These factors render DGK inhabitants highly vulnerable, severely exposed, and physically and structurally sensitive. As a result, these farmers have poor adaptive capacity because small impacts on these livestock enterprises disturb the existing balance of overall households' welfare within the mix of available resources [16].

### 3.5. Drivers Influencing Herders' Adaptations

Table 7 shows the results of drivers influencing livestock herders' adaptations to climate change. The results show that the coefficient of family size is positive and highly significant, which indicates that livestock herders with larger family size adopt more adaptations because of the accessibility of manpower required to manage the livestock. In addition, the coefficient of education is highly significant and positive, which emphasizes that educated livestock herders are likely to adopt more adaptations. The coefficient of household type is significant and positive, which indicates that households living in an extended/joint family type are likely to adopt more adaptations. The reason for this also relates to the family size; joint families have excess labor who are available to look after their livestock. The coefficient of cooking fuel is negative and only significant for the third adaptation. The overall negative sign indicates that smallholders have limited resources and suffer from financial constraints, and that if they used LPG as a cooking fuel, they did not have sufficient resources to spend on adaptations. The coefficient of off-farm work is negative and significant, indicating that off-farm work lessens the time allocation for livestock maintenance. Age, area under fodder, farm assets, and distance to market are non-significant, implying that these do not affect respondents' adoption behavior regarding climate change mitigation strategies.

Table 7. Drivers influencing livestock herders' adaptations to climate change.

| Explanatory Variables     | Response Variables |                    |                    |                    |
|---------------------------|--------------------|--------------------|--------------------|--------------------|
|                           | Model 1            | Model 2            | Model 3            | Model 4            |
| Age (years)               | −0.012 (0.017)     | −0.031 (0.025)     | −0.016 (0.023)     | −0.035 (0.028)     |
| Experience (years)        | 0.040 ** (0.017)   | 0.038 (0.026)      | 0.033 (0.024)      | 0.035 (0.029)      |
| Family Size (Persons)     | 0.070 ** (0.027)   | 0.051 ** (0.020)   | 0.059 *** (0.021)  | 0.059 *** (0.020)  |
| Education                 | 0.100 *** (0.033)  | 0.306 *** (0.047)  | 0.301 *** (0.045)  | 0.168 *** (0.047)  |
| Household type            | 0.211 *** (0.248)  | 1.076 *** (0.328)  | 1.127 *** (0.326)  | 0.606 * (0.364)    |
| Area under fodder (Acres) | 0.143 (0.130)      | 0.023 (0.129)      | −0.025 (0.122)     | 0.004 (0.121)      |
| Farm Assets (rumber)      | 0.106 (0.130)      | −0.158 (0.160)     | 0.020 (0.145)      | 0.197 (0.153)      |
| Cooking fuel              | −0.230 (0.346)     | −0.446 (0.444)     | −0.713 * (0.413)   | −0.090 (0.462)     |
| Basic repair facilities   | 0.610 ** (0.275)   | 0.307 (0.299)      | 1.199 *** (0.349)  | 1.246 *** (0.426)  |
| Off-farm income           | −0.532 * (0.287)   | −1.101 *** (0.352) | −1.041 *** (0.343) | −1.169 *** (0.380) |
| Distance to market (km)   | 0.013 (0.078)      | −0.001 (0.022)     | 0.018 (0.021)      | 0.028 (0.024)      |
| DGK                       | 0.503 (0.396)      | 1.931 *** (0.537)  | 0.385 (0.478)      | 0.424 (0.572)      |
| RYK                       | 0.585 (0.380)      | 1.751 *** (0.499)  | 0.633 (0.449)      | 1.171 ** (0.525)   |
| FSD                       | Omitted            | Omitted            | Omitted            | Omitted            |
| Constant                  | −2.139 ** (0.882)  | −3.932 *** (0.092) | −3.956 *** (1.005) | −4.270 *** (1.230) |
| Observations              | 405                | 405                | 405                | 405                |
| Pseudo R2                 | 0.143              | 0.251              | 0.295              | 0.244              |
| Log Likelihood            | −236.623           | −165.155           | −131.906           | −136.495           |
| Prob > chi2               | 0.0000             | 0.0000             | 0.0000             | 0.0000             |

Note: S.E reported in parentheses; \*\*\*, \*\*, \*, are significant at the  $p < 0.01$ ,  $p < 0.05$ ,  $p < 0.10$  level, respectively.

#### 4. Discussion

The majority of livestock herders perceived climate variability during the last ten years to be a major stimulus of increased vulnerability in the study area. More than 75% of respondents perceived a medium to high level of variations/patterns within the study district. This is expected because residents previously reported that numerous parts of the province experienced such impacts [16,37]. In the comparison of individuals' perceptions with the actual meteorological data of the recent past, to confirm if the former were supported by evidence, we found a genuine link between the former and the latter [16]. Respondents also reported the need for equipment and financial/technical support to help in adopting climate-smart practices to achieve sustained farm production, and to secure and diversify their livelihoods. In the study locations, CC mitigation measures were inadequate due to widespread poverty among respondents, who largely depended on livestock for subsistence. This inadequacy was exacerbated by lower education status, a poor resource base, and constrained institutional support. Given these factors, outside support from NGOs, and public and private sectors, is necessary for the implementation of effective adaptations, which will achieve and demonstrate benefits for poorer areas or those living in the vicinity [34,70,83]. The limited adaptation ability of rural households may be further complicated by the multiplier effect due to the declining productivity per unit of land. This results in a problem of food insecurity for the households themselves and urban consumers, thus leading to a decline in health status. In turn, this places significant pressure on foreign exchange to fulfil domestic demand via imports [84]. This circle will continue until households are capable of improving their self-efficacy to adopt CC measures [70]. As reported by Rivera-Ferre et al. [85], adoption of new strategies can improve production and food availability.

The previous literature has noted that rural people who are associated with the farming sector are severely affected by the negative impact of CC [86,87]. Ahmad and Ma [16] reported similar findings, which indicated that a decrease in precipitation, longer summers, and variations in the growing season were verified by farming communities. The magnitude and frequency of climatic extremes such as floods, droughts, and temperature fluctuations have been anticipated and are realized in recent years [59,88]. Numerous researchers have argued that environmental factors are not only responsible for vulnerability, but also the poverty levels of countries [41,52,89,90]. Moreover, the majority of the populations in developing countries rely on small-scale livelihoods, and have lower adaptive capacity, which creates significant challenges in coping with CC [5]. Large populations of developing countries, including Pakistan, are poor and live in rural, disaster-prone areas. Strengthening institutions and providing economic support are the most-effective means to mitigate CC impacts under these scenarios.

The current investigation revealed that livestock herders in the three study zones observed regular shocks to their livelihood due to livestock diseases and deaths caused by extreme climatic events. In particular, they were often faced with low livestock productivity due to fodder shortages, herd size reductions, or livestock losses. They also experienced food insecurity due to low crop and livestock yields. The strategies adopted by the livestock herders were based on the reduction in livestock products' consumption. These results are in line with previous studies, in which significant impacts of CC on the livelihood of smallholders are reported [5,8]. The generation of additional income by engaging in off-farm activities or changing employment/work patterns is reported to be an effective response. These adaptive measures evidently help to moderate the negative impacts on livestock herders; however, this approach is considered unsatisfactory in conditions of severe insecurity [14]. Additionally, adaptive measures to earn additional income are considered insufficient due to inadequate opportunities for off-farm wage laborers due to their poor skill and knowledge capital [12,74]. Other reasons, such as poor infrastructure and lack of institutional services, may also impact households' motivation to engage in alternate earning opportunities [6]. Significant efforts are required to improve the livelihood of small livestock herders, with a special focus on increasing livestock productivity and reducing

the vulnerability of their livelihoods to climate-related risks through a variety of other interventions. These interventions may include the provision of improved or stress-tolerant breeds and species, improving the institutional capability (infrastructure, markets access, and basic facilities), and the provision of human resource capability (technical education and expertise). The results indicated that the provision of veterinary services to enhance technical skills in these vulnerable zones, and the promotion of training programs related to the best management practices for the adoption of new technology, helped to increase livestock productivity and reduce vulnerability. The presence of functional facilities—for example, social safety nets and access to credit during catastrophes—and education in new techniques, can provide the ability to mitigate risks and maintain livestock productivity. Appropriate policies and programs are required to provide alternative measures for livelihood support and livestock diversification to reduce farmers' vulnerability. Omerkhil et al. [8] and Jha et al. [91] stated that properly developed government-sponsored rural development programs have improved welfare overall because these programs further support the ability of smallholders to increase their resilience to negative impacts of climate change.

## 5. Conclusions

The present research evaluated the livelihood vulnerability (LVI,  $LVI_{IPCC}$ ) of small livestock herders of three agro-ecological zones of Punjab, Pakistan. The LVI is a suitable method for the assessment of critical factors in which equal weight is applied to all major components and sub-components, and provides a better means of comparing the indicators across different regions at the household level. Moreover, this approach can help policy makers to identify the most vulnerable zones, and to develop response policies for the allocation of maximum resources in areas that are prone to the challenges associated with climate change.

Based on the results, this study offers the following specific policy recommendations. First, in the DGK zone, the priority is to focus on food and health, human resource capability, and institutional capability. Second, FSD requires timely information regarding climatic variations and disease control precautions to reduce livestock losses, because it is expected that the livestock sector may grow more quickly than crop farming in the future. Third, RYK requires financial support, and technical and professional assistance, to curb climate vulnerability. Poor food and health conditions, sensitive livelihood conditions, and lower economic, institutional, and human resource capabilities, are the prime reasons for small livestock herders' vulnerability in the study region. The main risks are a high frequency of disease outbreaks, variations in rainfall patterns, and temperature changes due to CC. Therefore, it is vital to reduce the current and future livelihood vulnerability to climate-related risks of smallholder livestock herders by increasing their productivity and resilience to CC. This requires a small number of low-cost and local approaches, such as improving veterinary services, reinforcing informal social safety nets, and applying small-scale local infrastructure projects. These approaches may represent feasible, cost-effective, and sustainable decisions, and encourage the development of a mindset of low periodic costs and the minimum maintenance required. The vulnerability results show that a large number of small livestock herders who are vulnerable to CC need educational, economic, and institutional support to improve their coping capacity. The assessment of critical indicators identified more specific future policy directions to combat livelihood vulnerability. From the assessed indicators, the policy targets comprise food and health projects, awareness of climatic vulnerabilities, and institutional capabilities for under-developed zones. Therefore, it is crucial to increase the adaptive capacity of small villages at the local scale to increase the resiliency of smallholders to combat the global threat of CC.

## Study limitations

Different approaches can be used to measure vulnerability. In the present study, an index-based method was used to evaluate vulnerability. Although this is a practical approach to explore the conceptual framework and to monitor different trends, it has

certain limitations, as follows. (1) Due to the analytical approach, we were confined in the selection of variables, authentication of various measurement units, and calculation of relative weights. We did not include all of the components that may affect the vulnerability of the region because the necessary improvement required the construction of major and minor components of vulnerability to enable a comprehensive evaluation. (2) Respondents are better able to recall recent trends in atmospheric condition, rather than earlier changes during the past decade, and CC is a long-term phenomenon. (3) Multidimensional data to evaluate vulnerability was lacking because we were confined to the assessment of government-provided indicators only.

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**Institutional Review Board Statement:** This study has been approved by the Institutional Review Board of Huazhong Agricultural University, Wuhan, China.

**Informed Consent Statement:** During survey, filling out the questionnaire from respondent was done after reading the informed consent for inclusion in the study.

**Data Availability Statement:** Data may compromise the privacy of study participants and may not be shared publicly. Data are available upon request to the Xia Chunping, Professor in College of Economics and Management, Huazhong Agricultural University, Wuhan, China Email: xcp@mail.hzau.edu.cn.

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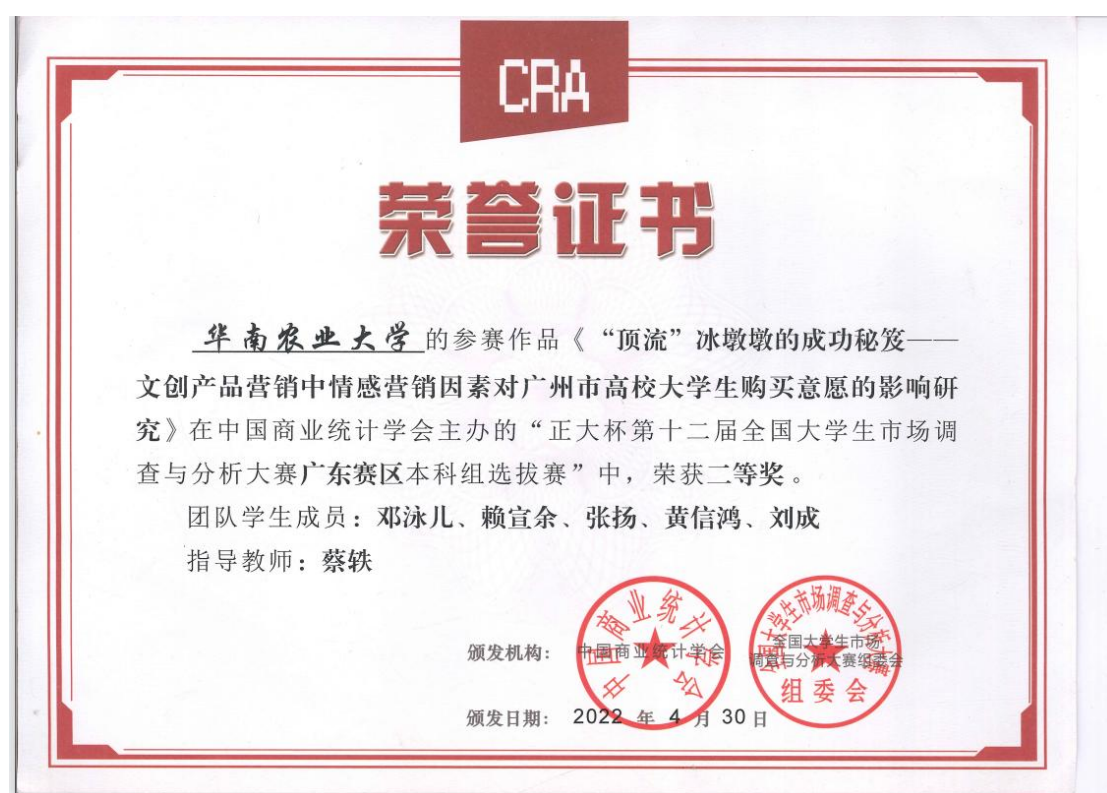
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## 四、其他业绩

### 1. 指导学生学科竞赛

1.1. 正大杯第十二届全国大学生市场调查与分析大赛广东赛区本科组选拔赛二等奖“‘顶流’冰墩墩的成功秘笈——文创产品营销中的情感营销因素对广州市搞笑大学生购买意愿的营销研究”



## 2. 社会服务

### (1) 2020 年度

①服务概览：在全国 3 个地区（广东省清远市、广西省平南镇）开展社会服务活动 3 场次，培训指导广州力智农业有限公司、清远市寻乡记智慧农业发展有限公司、广西藤县林桂贸易有限公司，深入访谈企业，提供管理咨询服务，加强了校企合作交流，累计服务 11 天。

②年度工作量：17 个工作量

### (2) 2021 年度

①服务概览：在全国 1 个地区（广东顺德市）开展社会服务活动 1 场次，累计服务 1 天，针对农村电商户开展信息进村入户培训，培训指导 150 人次。

②年度工作量：1 个工作量

### (3) 2023 年度

①服务概览：在全国 1 个地区（广西田林县）开展粤桂协作科技特派员项目活动 1 场次，培训指导百色市田林县利周瑶族乡爱善现代农业庄园，深入访谈企业，提供管理咨询服务，加强了校企合作交流，累计服务 12 天。

②年度工作量：12 个工作量

### (4) 2024 年度

①服务概览：在全国 1 个地区（广西田林县）开展粤桂协作科技特派员项目活动 1 场次，培训指导百色市田林

县利周瑶族乡爱善现代农业庄园，深入访谈企业，提供管理咨询服务，加强了校企合作交流，累计服务 3 天；培训指导广东省气象局，深入访谈，提供管理咨询服务，累计服务 1 天。

②年度工作量：6 个工作量