

申 报	系列：教师系列 教学科研并重 型
	专业：农业经济 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

目 录

一、教学研究业绩

1. 编写教材：《农业技术经济学》 4

二、科研项目

1. 主持：关于广东省哲学社会科学规划 2025 年度常规项目的立项通知（合同）及有关佐证材料..... 7
2. 主持：关于广州市哲学社会科学发展“十四五”规划 2025 年度课题的立项通知（合同）及有关佐证材料..... 10
3. 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..... 15
4. 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..... 18
5. 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..... 21
6. 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..... 25
7. 主参：关于广东省自然科学基金面上项目的立项通知（合同）及有关佐证材料..... 29

三、论文、著作等

1. 检索证明..... 32
2. 以第一作者发表本专业论文情况
2. 1. Effects of ICT-based extension service use on fertilizer knowledge and use efficiency: Evidence from litchi farmers in rural China..... 35
2. 2. Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China..... 46

2. 3. Impact of smartphone use on production outsourcing: evidence from litchi farming in southern China.....	64
2. 4. Mobile Internet adoption and technology adoption extensity: evidence from litchi growers in southern China.....	77
3. 以通讯作者发表本专业论文情况	
3. 1. E-commerce participation, digital finance and farmers' income.....	94
3. 2. The impact of e-commerce activities on rural household leverageThe impact of e-commerce activities on rural household leverage.....	114
3. 3. Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty.....	120
3. 4. Perceptions, vulnerability and adaptation strategies for mitigating climate change effects among small livestock herders in Punjab, Pakistan.....	134

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”	158
2. 社会服务.....	160

一、教学研究业绩

1. 编写教材：《农业技术经济学》



首批全国优秀出版社 | 中国农业出版社

图书在版编目 (CIP) 数据

农业技术经济学 / 蔡键主编. —北京: 中国农业出版社, 2023. 11

ISBN 978-7-109-31533-4

I. ①农… II. ①蔡… III. ①农业技术经济学—高等学校—教材 IV. ①F303.2

中国国家版本馆 CIP 数据核字 (2023) 第 238622 号

中国农业出版社出版

地址: 北京市朝阳区麦子店街 18 号楼

邮编: 100125

责任编辑: 夏之翠

版式设计: 杨 婧 责任校对: 吴丽婷

印刷: 三河市国英印务有限公司

版次: 2023 年 11 月第 1 版

印次: 2023 年 11 月河北第 1 次印刷

发行: 新华书店北京发行所

开本: 700mm×1000mm 1/16

印张: 15.75

字数: 287 千字

定价: 34.50 元

版权所有·侵权必究

凡购买本社图书, 如有印装质量问题, 我社负责调换。

服务电话: 010-59195115 010-59194918

编写人员名单

主 编 蔡 键

副主编 薛春玲

参 编 周 伟 石 敏 蔡 轶
易智敏 苏柳方

二、科研项目

1. 主持：关于广东省哲学社会科学规划 2025 年度常规项目的立项通知（合同）及有关佐证材料

广东省哲学社会科学规划专项小组

粤社科规专通〔2025〕16 号

广东省哲学社会科学规划 2025 年度 常规项目、三类研究专项立项通知书

蔡轶同志：

经省委宣传部批准，您申报的广东省哲学社会科学规划 2025 年度常规项目、三类研究专项《农村数字基础设施建设对家庭发展韧性的影响研究：效应、机制与政策优化》获准立项，项目类型为一般项目，批准号为 GD25CYJ31，资助经费 3.0 万元，将分两次拨付至项目负责人所在单位账户，第一次拨款 2.7 万元，待通过结项鉴定后再拨付预留经费 0.3 万元。

项目负责人所在单位须承担保证责任。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》（粤宣发〔2024〕5号）《广东省省级财政社会科学研究项目资金的管理监督办法》（粤财规〔2023〕2号）。对于出现违规行为的，省哲学社会科学规划专项小组将依据相关规定进行处理。

2. 批准后的项目经费不再追加，课题组可以不接受，而一经接受，将不能以经费不足为由，擅自变更原设计的最终成果形式和内容。

3. 项目立项后，课题组须按项目申请书所列计划开展研究。研究过程中，如有变更项目负责人、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、延期等重要事项，项目负责人或所在单位必须及时在广东省哲学社会科学规划项目管理平台申请变更，线上报省哲学社会科学规划专项小组审批。

4. 省社科规划项目成果为论文的，在公开发表时必须注明“广东省哲学社会科学规划项目（项目编号）”字样。成果（含阶段成果）为专著、研究报告的，未经省哲学社会科学规划专项小组组织专家鉴定的，出版时不能标明“广东省哲学社会科学规划项目（项目编号）”字样；如成果确实有先出版后鉴定结项的需要，必须先向省哲学社会科学规划专项小组提出书面申请，经批准后才能出版。

并标明“广东省哲学社会科学规划项目（项目编号）”字样；如未经鉴定申请，自行出版并标明“广东省哲学社会科学规划项目（项目编号）”字样，省哲学社会科学规划专项小组不接受项目结项申请并予以撤项处理。

5. 项目负责人及所在单位须在规定时间内向省哲学社会科学规划专项小组提交项目结项材料。规定时间内不提交结项材料的将作撤项处理。结项所需材料、装印要求等具体事项，请登录广东社科规划网站“结项信息”栏目查看。

6. 成果鉴定等级分为优秀、良好、合格和不合格四个等次。通过结项的，将拨付预留经费。不合格即未能通过结项的，课题组需修改后半年内重新申请结项鉴定。仍不能通过的，将作撤项处理，不再拨付预留经费。

7. 被撤项的项目负责人五年内不得申报国家社科基金项目和省哲学社会科学规划项目。

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，立项协议自行废止。

2. 主持：关于广州市哲学社会科学发展“十四五”规划 2025 年度课题的立项通知（合同）及有关佐证材料

课题编号	2025GZQN17
------	------------

广州市哲学社会科学发展“十四五”规划

2025 年度课题协议

二〇二五年八月

甲方（课题下达单位）

单位名称：广州市社会科学规划领导小组办公室

/广州市社会科学界联合会

联系地址：广州市天河区龙口东路 363 号宝供大厦二楼

法定代表人：崔颂东

单位联系电话：020-89815149

乙方（课题负责人）

姓 名：蔡轶

身份证号：

联系地址：广东省广州市天河区五山路 483 号华南农业大学

联系电话：

丙方（课题承担单位）

单位名称：华南农业大学

联系地址：广东省广州市天河区五山路 483 号华南农业大学

法定代表人：薛红卫

单位联系电话：020-85280070

一、经专家组评审，报广州市委宣传部审定，同意将乙方申

报的课题“农村数字基础设施建设的共同富裕效应与优化对策研究”立项为广州市社科规划 2025 年度羊城青年学人课题。课题编号：2025GZQN17，课题负责人蔡轶，课题组成员洪炜杰、陈洋、程广州、杜兴文。

二、课题经费管理

课题经费管理严格按照国家、广东省、广州市有关科研管理经费的最新文件精神执行，日常管理由丙方负责。课题立项初期甲方向乙方资助启动经费 1 万元，拨付至丙方（开户银行账户名：中国工商银行广州五山支行，开户银行账号：3602 0026 0900 0310 520）。根据结项等级划拨后期经费，一等 2 万元，二等 1 万元，三等不再拔付经费。提交结项材料不符合要求或逾期结项的课题不参与等级评审，不追加经费。



三、课题结项要求

1. 结项时间. 2027 年 5 月 30 日前完成并向甲方提交结项材料。

2. 结项条件. 完成课题申报书研究任务，并满足以下条件之一即可申请结项：

（1）成果形式为研究报告的：须提交 1 篇反映课题涉及领域基本情况、基础数据的深度调研报告，且课题成果（最终成果或

阶段性成果)获各级党委政府或者各级党政职能部门吸收借鉴,有相关证明。

(2)成果形式为论文的:至少1篇C扩论文或其他同类报刊理论文章,或2篇普刊论文。

(3)成果形式为专著的:已正式出版。

3.结项材料。需提交纸质结项材料:①结题报告书原件;②课题申报书、课题立项协议复印件;③研究成果;④佐证材料。并发送以上材料电子版至广州市社科规划办邮箱 gzsgbh@163.com。具体整理及装订要求参见结项当年广州市社科规划办公布的结项材料整理要求。

四、乙方必须遵守《广州市哲学社会科学“十四五”规划课题管理办法》,认真开展课题研究,恪守学术规范,不弄虚作假,保证取得预期研究成果。如乙方无故终止课题研究,按相关规定进行处理。

五、乙方研究成果对外发表或出版以及报送相关部门,应标注“广州市哲学社会科学‘十四五’规划课题”字样和课题编号。

六、乙方研究成果应确保无涉密及涉意识形态问题。乙方研

究成果对外发表或出版，以及报送相关部门前，应报丙方审查。

七、《课题立项协议》一式三份，一份由甲方保存，一份由乙方保存，一份由丙方科研管理部门保存。

甲方：广州市社会科学规划领导小组办公室/广州市社会科学界联合会（盖章）

法定代表人或委托人（签字）


陈璐

日期：2025 年 8 月 7 日

乙方：_____蔡轶____（课题负责人）

课题负责人（签字）：



日期：2025 年 8 月 7 日

丙方：____华南农业大学____（单位盖章）

法定代表人或委托人（签字）


蔡轶

日期：2025 年 8 月 7 日

3. 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

邮编：510635

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

4. 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

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。

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	艺术教育与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

5. 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。
2. 本任务书要求按照已给的格式，5号宋体字填写，单倍行间距，段落间无间距，A4纸双面打印。
3. 本任务书封面不签字盖章，仅在签约方页签字盖章。
4. 本任务书可视填报内容自行增加页码。
5. 本任务书由国家荔枝龙眼产业技术研发中心统一编号，一式4份，国家荔枝龙眼产业技术研发中心依托单位1份，首席科学家1份，岗位科学家1份，岗位科学家依托单位1份。

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					
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	
贺梅英	研究生/副教授	1977-12	女	华南农业大学	
杨学儒	研究生/教授	1980-05	男	华南农业大学	
蔡轶	研究生/副教授	1990-10	男	华南农业大学	

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

6. 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；
3. **2022年10月19日：**报送纸质版计划书（一式两份，其中一份包含申请书纸质签字盖章页）的截止时间。
4. **2022年10月28日：**报送修改后的申请书纸质签字盖章页的截止时间。

请按照以上规定及时提交电子版计划书，并报送纸质版计划书和申请书纸质签字盖章页，逾期不报计划书或申请书纸质签字盖章页且未说明理由的，视为自动放弃接受资助；未按要求修改或逾期提交申请书纸质签字盖章页者，将视情况给予暂缓拨付经费等处理。

附件：项目评审意见及修改意见表

国家自然科学基金委员会

2022年9月7日



项目批准号	72273046
申请代码	G0311
归口管理部门	
依托单位代码	51064208A0499-0932



722730461005837

国家自然科学基金 资助项目计划书 (预算制项目)

资助类别: 面上项目

亚类说明:

附注说明:

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: 44万元 执行年限: 2023.01-2026.12

负责人: 张蓓

通讯地址: 广东省广州市天河区五山路483号华南农业大学经济管理学院

邮政编码: 510642 电 话: 020-85283551

电子邮件: windy Zhang@139.com

依托单位: 华南农业大学

联系人: 唐家林 电 话: 020-85280070

填表日期: 2022年09月09日

国家自然科学基金委员会制

Version: 1.005.837



项目组主要成员

编号	姓名	出生年月	性别	职称	学位	单位名称	电话	证件号码	项目分工	每年工作 时间 (月)
1	张蓓	1978.04	女	教授	博士	华南农业大学			项目负责人	9
2	周文良	1971.01	男	副教授	博士	华南农业大学			理论分析、对策研 究	7
3	蔡铁	1991.08	男	讲师	博士	华南农业大学			模型设计、实证分 析	8
4	文乐	1988.02	男	讲师	博士	华南农业大学			对策研究、实证分 析	8
5	彭思喜	1978.08	男	讲师	硕士	华南农业大学			问卷调查、深度访 谈	8
总人数		高级		中级		初级	博士后	博士生	硕士生	
12		2		3				2	5	

7. 主参：关于广东省自然科学基金面上项目的立项通知（合同）及有关佐证材料

广东省基础与应用基础研究基金项目任务书

受理编号：c23140500001066

项目编号：2023A1515011263

文件编号：粤基金字（2023）2号

广东省基础与应用基础研究基金项目
任务书

项目名称：基于大数据赋能的农业企业组织韧性提升机制及对策研究

项目类别：广东省自然科学基金-面上项目

项目起止时间：2023-01-01 至 2025-12-31

管理单位（甲方）：广东省基础与应用基础研究基金委员会

依托单位（乙方）：华南农业大学

通讯地址：广东省广州市天河区五山路483号

邮政编码：510642

单位电话：020-85283435

项目负责人：林家宝

联系电话：020-85283551



（广东科技微信公众号）



（查看任务书信息）



（受理纸质材料二维码）

广东省基础与应用基础研究
基金委员会
二〇二〇年制

五、人员信息

项目负责人								
姓名	证件号码	年龄	性别	职称	学历	在项目中承担的任务	所在单位	签名
林家宝		41	男	教授	博士研究生	项目负责人	华南农业大学	林家宝
项目组主								
姓名		年龄	性别	职称	学历	在项目中承担的任务	所在单位	签名
蔡轶		32	男	讲师	博士研究生	理论分析	华南农业大学	蔡轶
龙思颖		33	女	讲师	博士研究生	实证研究	华南农业大学	龙思颖
伍敬文		31	女	讲师	博士研究生	实证研究	华南农业大学	伍敬文
郭金沅		28	男	未取得	硕士研究生	数据收集与分析	华南农业大学	郭金沅
林顺芝		27	女	未取得	本科	数据收集与分析	华南农业大学	林顺芝
郑钦耀		26	男	未取得	本科	数据收集与分析	华南农业大学	郑钦耀
吴少武		24	男	未取得	本科	数据收集与分析	华南农业大学	吴少武

六、工作分工及财政经费分配

承担/参与单位名称 (盖章)	工作分工	省级财政科技资金分配 (万元)
华南农业大学	负责本项目的组织、协调、管理与保障。	10.00
	合计	10.00

检索证明

根据委托人提供的论文材料，委托人华南农业大学经济管理学院蔡秩 8 篇论文收录情况如下表。

序号	论文名称	发表刊物及发表的年月卷期/页码等	作者排名	论文等级	作者文中单位	收录情况	影响因子	中科院大类分区
1	Effects of ICT-based extension service use on fertilizer knowledge and use efficiency: Evidence from litchi farmers in rural China	ENVIRONMENTAL DEVELOPMENT 出版年: 2024 出版日期: MAR 卷期: 49 页码: - 文献号: 100944 文献类型: Article	1	A类	华南农业大学 经济管理学院	SCI	IF2-year=5.3 IF5-year=5.7 (2024)	环境科学与生态学 2 区 Top 期刊: 否 (2025)
2	Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China	AGRI-BUSINESS 出版年: 2023 出版日期: JAN 卷期: 39 1 页码: 131-147 文献类型: Article	1	B类	华南农业大学 经济管理学院	SCI	IF2-year=2.1 IF5-year=2.7 (2023)	经济学 3 区 Top 期刊: 否 (2023)
3	Impact of smartphone use on production outsourcing: evidence from litchi farming in southern China	INTERNATIONAL FOOD AND AGRIBUSINESS MANAGEMENT REVIEW 出版年: 2022 卷期: 25 4 页码: 671-682 文献类型: Article	1	无	华南农业大学 经济管理学院	SCI	IF2-year=1.5 IF5-year=1.6 (2022)	经济学 4 区 Top 期刊: 否 (2022)

三、论文、著作等
1. 检索证明

4	Mobile Internet adoption and technology adoption extensivity: evidence from litchi growers in southern China	CHINA AGRICULTURAL ECONOMIC REVIEW 出版年: 2022 出版日期: JAN 17 卷期: 14 1 页码: 106-121 文献类型: Article	1	B类	华南农业大学 经济管理学院	SCI	IF2-year=5.1 IF5-year=4.6 (2022)	经济学 3 区 Top 期刊: 否 (2022)
5	E-commerce participation, digital finance and farmers' income	CHINA AGRICULTURAL ECONOMIC REVIEW 出版年: 2023 出版日期: DEC 1 卷期: 15 4 页码: 833-852 文献类型: Article	通讯作者	A类	华南农业大学 经济管理学院	SCI	IF2-year=4.4 IF5-year=4.9 (2023)	经济学 2 区 Top 期刊: 否 (2023)
6	The impact of e-commerce activities on rural household leverage	APPLIED ECONOMICS 出版年: 2024 出版日期: MAR 11 卷期: 31 5 页码: 461-464 文献类型: Article	通讯作者	C类	华南农业大学 经济管理学院	SSCI	IF2-year=1.3 IF5-year=1.3 (2024)	经济学 4 区 Top 期刊: 否 (2025)
7	Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty	CLIMATE RISK MANAGEMENT 出版年: 2021 卷期: 34 页码: - 文献号: 100358 文献类型: Article	共同通讯作者 (倒数第一)	B类	华南农业大学 经济管理学院	SSCI	IF2-year=5.266 IF5-year=7.777 (2021)	环境科学与生态学 2 区 Top 期刊: 否 (2021)

8	Perceptions, Vulnerability and Adaptation Strategies for Mitigating Climate Change Effects among Small Livestock Herders in Punjab, Pakistan	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH 出版年: 2021 出版日期: OCT 卷期: 18 20 页码: - 文献号: 10771 文献类型: Article	通讯作者	C类	华南农业大学 经济管理学院	SCI	IF2-year=4.614 IF5-year=4.799 (2021)	医学 3区 Top 期刊: 否 (2021)
---	--	---	------	----	------------------	-----	--	------------------------------

说明: 论文等级和中科院大类分区按《华南农业大学学术论文集评价方案(试行)》划分。

报告免责声明: 如未盖章, 报告无效



华南农业大学图书馆

2. 以第一作者发表本专业论文情况

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





Environmental Development

Supports open access

7.8
CiteScore

5.4
Impact Factor

[Articles & Issues](#)
[About](#)
[Publish](#)
[Order journal](#)

Search in this journal

[Submit your article](#)
[Guide for authors](#)

Volume 49

In progress (March 2024)

This issue is in progress but contains articles that are final and fully citable.

[Download full issue](#)

[< Previous vol/issue](#)
[Next vol/issue >](#)

Actions for selected articles

Select all / Deselect all

[Download PDFs](#)

[Export citations](#)

☐ Show all article previews

Contents

[Editorial](#)

[Research Paper](#)

[Review Article](#)

Receive an update when the latest issues in this journal are published

[Sign in to set up alerts](#)

[FEEDBACK](#)

Editorial

☐ Editorial • Full text access

Localized governance of carbon dioxide removal in small island developing states

H. Hilber, E. Cox, C. Moreau, L. Hiraldo, ... N.G. Walworth

Article 100942

[View PDF](#)
[Article preview](#)

Research Paper

☐ Research article • Full text access

Vulnerability of communities' livelihoods to the impacts of climate change in north-western highlands of Tanzania

Edmund B. Mubhaya

Article 100939

[View PDF](#)
[Article preview](#)

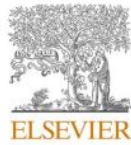
☐ Research article • Full text access

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

Yi Cai, Wene Qi, Famin Yi

Article 100944

[View PDF](#)
[Article preview](#)



Contents lists available at ScienceDirect

Environmental Development

journal homepage: www.elsevier.com/locate/envdev

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

Yi Cai ^{a,b,c}, Wene Qi ^{a,*}, Famin Yi ^{a,c}^a College of Economics and Management, South China Agricultural University, Guangzhou, China^b Research Center for Green Development of Agriculture, South China Agricultural University, Guangzhou, China^c Digital Countryside Research Institute, South China Agricultural University, Guangzhou, China

ARTICLE INFO

Keywords:

ICT-based extension service
Fertilizer knowledge
Fertilizer use efficiency
Litchi farmer
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 (P₂O₅), and potash (K₂O) 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

* Corresponding author.

E-mail address: qiwene@scau.edu.cn (W. Qi).<https://doi.org/10.1016/j.envdev.2023.100944>

Received 1 February 2023; Received in revised form 16 September 2023; Accepted 9 November 2023

Available online 15 November 2023

2211-4645/© 2023 Published by Elsevier B.V.

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

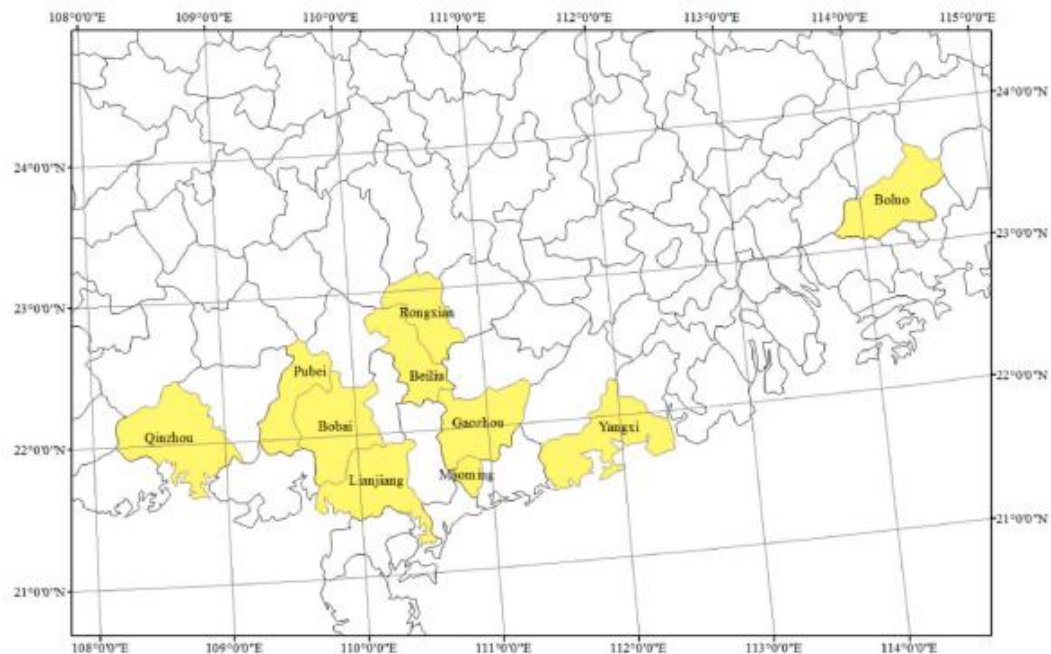


Fig. 1. Survey areas.

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 (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 (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 β 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 θ 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
λ	1.278***	0.075
σ	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 σ_v^2 is defined in Equation (1) and σ_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_{IW}) is higher than that of not using IES (U_{IN}). However, in an observational study, the utility difference ($T_i^* = U_{IW} - U_{IN}$) 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, α_i is a constant, θ_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):

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

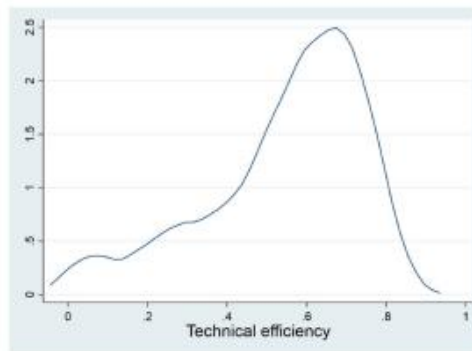


Fig. 2. Kernel density distribution of technical efficiency.

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 λ 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.

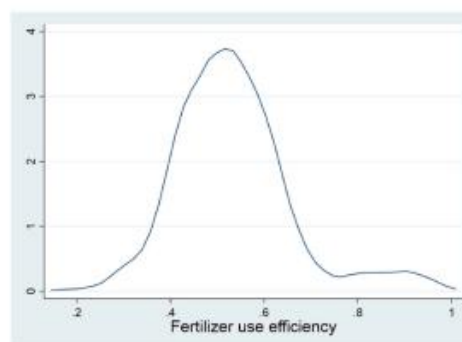


Fig. 3. Kernel density distribution of fertilizer use efficiency.

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

This study was supported by China Agriculture Research System of MOF and MARA (CARS-32-14), the Youth Project of Guangdong Provincial Department of Education (2020WQNCX006), and the Social Science Fund of Guangdong (GD21YYJ06), and the National Social Science Fund of China (19BGL256).

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.

References

- Aker, J.C., 2011. Dial "A" for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agric. Econ.* 42 (6), 631–647. <https://doi.org/10.1111/j.1574-0862.2011.00545.x>.
- Aker, J.C., Ghosh, I., Burrell, J., 2016. The promise (and pitfalls) of ICT for agriculture initiatives. *Agric. Econ.* 47 (S1), 35–48. <https://doi.org/10.1111/agec.12301>.

- Arouna, A., Michler, J.D., Yergo, W.G., Saito, K., 2021. One size fits all? Experimental evidence on the digital delivery of personalized extension advice in Nigeria. *Am. J. Agric. Econ.* 103 (2), 596–619. <https://doi.org/10.1111/ajae.12151>.
- Bai, X., Wang, Y., Huo, X., Salim, R., Bloch, H., Zhang, H., 2019. Assessing fertilizer use efficiency and its determinants for apple production in China. *Ecol. Indic.* 104, 268–278. <https://doi.org/10.1016/j.ecolind.2019.05.006>.
- Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empir. Econ.* 20 (2), 325–332. <https://doi.org/10.1007/BF01205442>.
- Chen, H.B., Huang, X.M., 2014. Overview of Litchi Production in the World with Specific Reference to China.
- Ding, J., Li, J., Liu, J., Zhang, W., Jia, X., 2022. ICT-based agricultural advisory services and nitrogen management practices: a case study of wheat production in China. *J. Integr. Agric.* 21 (6), 1799–1811. [https://doi.org/10.1016/S2095-3119\(21\)63859-5](https://doi.org/10.1016/S2095-3119(21)63859-5).
- Fu, X., Akter, S., 2016. The impact of mobile phone technology on agricultural extension services delivery: evidence from India. *J. Dev. Stud.* 52 (11), 1561–1576. <https://doi.org/10.1080/00220388.2016.1146700>.
- Goldfarb, A., Prince, J., 2008. Internet adoption and usage patterns are different: implications for the digital divide. *Inf. Econ. Pol.* 20 (1), 2–15. <https://doi.org/10.1016/j.infoecopol.2007.05.001>.
- Huang, J., Hu, R., Cao, J., Rozelle, S., 2008. Training programs and in-the-field guidance to reduce China's overuse of fertilizer without hurting profitability. *J. Soil Water Conserv.* 63, 165A–167A.
- Huang, J., Huang, Z., Jia, X., Hu, R., Xiang, C., 2015. Long-term reduction of nitrogen fertilizer use through knowledge training in rice production in China. *Agric. Syst.* 135, 105–111. <https://doi.org/10.1016/j.agryst.2015.01.004>.
- Huang, J., Xiang, C., Jia, X., Hu, R., 2012. Impacts of training on farmers' nitrogen use in maize production in Shandong, China. *J. Soil Water Conserv.* 67, 321–327.
- Jia, X.-p., Huang, J.-k., Xiang, C., Hou, L.-k., Zhang, F.-s., Chen, X.-p., Bergmann, H., 2013. Farmer's adoption of improved nitrogen management strategies in maize production in China: an experimental knowledge training. *J. Integr. Agric.* 12 (2), 364–373. [https://doi.org/10.1016/S2095-3119\(13\)60237-3](https://doi.org/10.1016/S2095-3119(13)60237-3).
- Ju, X.-T., Xing, G.-X., Chen, X.-P., Zhang, S.-L., Zhang, L.-J., Liu, X.-J., Zhang, F.-S., 2009. Reducing environmental risk by improving N management in intensive Chinese agricultural systems. *Proc. Natl. Acad. Sci. USA* 106 (9), 3041–3046. <https://doi.org/10.1073/pnas.0813417106>.
- Kaiser, F.G., Fuhrer, U., 2003. Ecological behavior's dependency on different forms of knowledge. *Appl. Psychol.: Int. Rev.* 52 (4), 598–613. <https://doi.org/10.1111/1464-0597.00153>.
- Khanal, A.R., Mishra, A.K., 2016. Financial performance of small farm business households: the role of internet. *China Agric. Econ. Rev.* 8 (4), 553–571. <https://doi.org/10.1108/CAER-12-2014-0147>.
- Kiiza, B., Pederson, G., 2012. ICT-based market information and adoption of agricultural seed technologies: insights from Uganda. *Telecommun. Pol.* 36 (4), 253–259. <https://doi.org/10.1016/j.telpol.2012.01.001>.
- Larochelle, C., Alwang, J., Travis, E., Barrera, V.H., Domínguez Andrade, J.M., 2019. Did you really get the message? Using text reminders to stimulate adoption of agricultural technologies. *J. Dev. Stud.* 55 (4), 548–564. <https://doi.org/10.1080/00220388.2017.1393522>.
- Linden, A., Uysal, S.D., Ryan, A., Adams, J.L., 2016. Estimating causal effects for multivalued treatments: a comparison of approaches. *Stat. Med.* 35 (4), 534–552. <https://doi.org/10.1002/sim.6768>.
- Ma, L., Feng, S., Reidsma, P., Qu, F., Heerink, N., 2014. Identifying entry points to improve fertilizer use efficiency in Taihu Basin, China. *Land Use Pol.* 37, 52–59. <https://doi.org/10.1016/j.landusepol.2013.01.008>.
- Ma, W., Zheng, H., 2022. Heterogeneous impacts of information technology adoption on pesticide and fertilizer expenditures: evidence from wheat farmers in China. *Aust. J. Agric. Resour. Econ.* 66 (1), 72–92. <https://doi.org/10.1111/1467-9489.12446>.
- Ogutu, S.O., Okello, J.J., Otieno, D.J., 2014. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: the case of Kenya. *World Dev.* 64, 311–321. <https://doi.org/10.1016/j.worlddev.2014.06.011>.
- Pan, D., Kong, F., Zhang, N., Ying, R., 2017. Knowledge training and the change of fertilizer use intensity: evidence from wheat farmers in China. *J. Environ. Manag.* 197, 130–139. <https://doi.org/10.1016/j.jenvman.2017.03.069>.
- Pan, D., Zhang, N., 2018. The role of agricultural training on fertilizer use knowledge: a randomized controlled experiment. *Ecol. Econ.* 148, 77–91. <https://doi.org/10.1016/j.ecolecon.2018.02.004>.
- Redman, E., Redman, A., 2014. Transforming sustainable food and waste behaviors by realigning domains of knowledge in our education system. *J. Clean. Prod.* 64, 147–157. <https://doi.org/10.1016/j.jclepro.2013.09.016>.
- Reinhard, S., Lovell, C.A.K., Thijssen, G., 1999. Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms. *Am. J. Agric. Econ.* 81 (1), 44–60. <https://doi.org/10.2307/1244449>.
- Uysal, S.D., 2015. Doubly robust estimation of causal effects with multivalued treatments: an application to the returns to schooling. *J. Appl. Econ.* 30 (5), 763–786. <https://doi.org/10.1002/jae.2386>.
- Wu, Y., 2011. Chemical fertilizer use efficiency and its determinants in China's farming sector: implications for environmental protection. *China Agric. Econ. Rev.* 3, 117–130.
- Yuan, F., Tang, K., Shi, Q., 2021. Does Internet use reduce chemical fertilizer use? Evidence from rural households in China. *Environ. Sci. Pollut. Control Ser.* 28 (5), 6005–6017. <https://doi.org/10.1007/s11356-020-10944-4>.

Yi Cai is an assistant professor, Wene Qi is an associate professor, and Famin Yi is a professor in the College of Economics and Management, Research Center for Green Development of Agriculture, Digital Countryside Research Institute, South China Agricultural University, Guangzhou, China. Wene Qi (qwene@scau.edu.cn) is the Corresponding author.

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

Agribusiness	
An International Journal	
Volume 39, Number 1	Winter 2023
CONTENTS	
Research Articles	
• Behavioral framing and consumer acceptance of new food technologies: Factors influencing consumer demand for active packaging David R. Just and Julie M. Goddard	3
• Toward a differentiated understanding of the effect of Nutri-Score nutrition labeling on healthier food choices Birgit Gassler, Claudia K. Faesl, and Anke Moeser	28
• I scream, you scream, we all scream for local ice cream: Consumer preferences for locally processed foods Xiao Dong, H. Allen Klaiber, and Zoë Plakias	51
• Exploring market choices in the US ornamental horticulture industry Xuan Wei, Hayk Khachatryan, Alan Hodges, Charlie Hall, Marco Palma, Ariana Torres, and Robin Brumfield	65
• Factors correlated with the propensity to use automation and mechanization by the US nursery industry Alicia L. Rihn, Margarita Velandia, Laura A. Warner, Amy Fulcher, Susan Schexnayder, and Anthony LeBude	110
• Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China Yi Cai, Wene Qi, and Famin Yi	131
• Dynamic modeling of biotechnology adoption with individual versus social learning: An application to US corn farmers Do-Il Yoo and Jean-Paul Chavas	148
• Domestic clustered networks and internationalization of agrifood SMEs Raul Serrano, Natalia Dejo-Orlcalin, Juan Ferrer, Vicente Pinilla, Silvia Abella-Garcés, and María Teresa Maza	167
• Big and strong or small and beautiful: Effects of organization size on the performance of farmer cooperatives in China Qiao Liang, Rongrong Bai, Zhi Jin, and Linlin Fu	196
• Forecasting drinking milk price based on economic, social, and environmental factors using machine learning algorithms Abdulkadir Abalan	214
• Do smaller chicken farms use more antibiotics? Evidence of antibiotic diffusion from Nigeria Charuta M. Parkhi, Lenis Saweda O. Liverpool-Tasle, and Thomas Reardon	242
• Multiplicity of sustainability standards and potential trade costs in the palm oil industry Laura M. G. Hidalgo, Rosane N. de Faria, Roberta Souza Piao, and Christine Wieck	263
Letters	
• Effectiveness of nutritional information in increasing demand for enriched yoghurt among poor households in Kenya: Implications for agribusiness marketing strategies David L. Ortega, Vincenzina Caputo, and Mywish Maredia	285
• The impact of the Russian invasion of Ukraine on grain and oilseed trade Soojung Ahn, Dongin Kim, and Sandro Steinbach	291
WILEY	ISSN 0742-4477

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

Yi Cai^{1,2,3}  | Wene Qi¹ | Famin Yi^{1,3}

¹College of Economics and Management, South China Agricultural University, Guangzhou, China

²Research Center for Green Development of Agriculture, South China Agricultural University, Guangzhou, China

³Digital Countryside Research Institute, South China Agricultural University, Guangzhou, China

Correspondence

Wene Qi, College of Economics and Management, South China Agricultural University, 483 Wushan Rd, 510640 Guangzhou, China.
Email: qiwen@scau.edu.cn

Funding information

National Office for Philosophy and Social Sciences, Grant/Award Number: 19BGL256; The Youth Project of Guangdong Provincial Department of Education, Grant/Award Number: 2020WQNCX006; The earmarked fund for China Agriculture Research System, Grant/Award Number: CARS-32-14; The Social Science Fund of Guangdong, Grant/Award Number: GD21YYJ06

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, γ_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.), β_{1i} and β_{0i} are vectors of parameters, and ε_{1i} and ε_{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 ϕ_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, ρ_0 is the correlation between ε_{0i} and u_i , and ρ_1 is the correlation between ε_{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; Hübler & 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)
ρ_1		-0.587* (0.306)	
ρ_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 > χ^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 ρ_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 ε_{0i} (ε_{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.

ACKNOWLEDGMENTS

This study was supported by China Agriculture Research System of MOF and MARA (CARS-32-14), the Youth Project of Guangdong Provincial Department of Education (2020WQNCX006), and the Social Science Fund of Guangdong (GD21YYJ06), and the National Social Science Fund of China (19BGL256).

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.

ORCID

Yi Cai  <http://orcid.org/0000-0002-8632-8706>

REFERENCES

- Aakvik, A., Heckman, J. J., & Vytlacil, E. J. (2005). Estimating treatment effects for discrete outcomes when responses to treatment vary: An application to Norwegian vocational rehabilitation programs. *Journal of Econometrics*, 125(1), 15–51. <https://doi.org/10.1016/J.JECONOM.2004.04.002>
- Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, 2(3), 46–59.
- Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, 42(6), 631–647.
- Aker, J. C., Ghosh, I., & Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, 47(51), 35–48. <https://doi.org/10.1111/agec.12301>
- Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, 60, 44–51.
- Annosi, M. C., Brunetta, F., Monti, A., & Nati, F. (2019). Is the trend your friend? An analysis of technology 4.0 investment decisions in agricultural SMEs. *Computers in Industry*, 109, 59–71. <https://doi.org/10.1016/J.COMPIND.2019.04.003>
- Arouna, A., Michler, J. D., Yergo, W. G., & Saito, K. (2021). One size fits all? Experimental evidence on the digital delivery of personalized extension advice in Nigeria. *American Journal of Agricultural Economics*, 103(2), 596–619. <https://doi.org/10.1111/AJAE.12151>
- Barnes, A., Soto, I. D., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., Van der Wal, T., & Gómez-Barbero, M. (2019). Influencing factors and incentives on the intention to adopt precision agricultural technologies within arable farming systems. *Environmental Science & Policy*, 93, 66–74. <https://doi.org/10.1016/J.ENVSCI.2018.12.014>
- Batte, M. T., & Arnholt, M. W. (2003). Precision farming adoption and use in Ohio: Case studies of six leading-edge adopters. *Computers and Electronics in Agriculture*, 38(2), 125–139. [https://doi.org/10.1016/S0168-1699\(02\)00143-6](https://doi.org/10.1016/S0168-1699(02)00143-6)
- Busse, M., Doernberg, A., Siebert, R., Kuntosch, A., Schwerdtner, W., König, B., & Bokelmann, W. (2013). Innovation mechanisms in German precision farming. *Precision Agriculture*, 15, 403–426.
- Camphenout, B. V. (2017). There is an app for that? The impact of community knowledge workers in Uganda. *Information Communication & Society*, 20(4), 530–550. <https://doi.org/10.1080/1369118X.2016.1200644>
- Camphenout, B. V., Spielman, D. J., & Lecoutere, E. (2021). Information and communication technologies to provide agricultural advice to smallholder farmers: Experimental evidence from Uganda. *American Journal of Agricultural Economics*, 103(1), 317–337. <https://doi.org/10.1002/AJAE.12089>
- Carter, D. W., & Milon, J. W. (2005). Price knowledge in household demand for utility services. *Land Economics*, 81(2), 265–283. <https://doi.org/10.3368/LE.81.2.265>
- Chuang, J.-H., Wang, J.-H., & Liang, C. (2020). Implementation of Internet of Things depends on intention: Young farmers' willingness to accept innovative technology. *The International Food and Agribusiness Management Review*, 23(2), 253–265. <https://doi.org/10.22434/IFAMR2019.0121>
- Chuang, J.-H., Wang, J.-H., & Liou, Y.-C. (2020). Farmers' knowledge, attitude, and adoption of smart agriculture technology in Taiwan. *International Journal of Environmental Research and Public Health*, 17(19), 7236. <https://doi.org/10.3390/IJERPH17197236>
- Cole, S. A., & Fernando, A. N. (2021). 'Mobile'izing agricultural advice: technology adoption diffusion and sustainability. *The Economic Journal*, 131(633), 192–219. <https://doi.org/10.1093/EJ/UEAA084>
- Cui, M., Pan, S. L., Newell, S., & Cui, L. (2016). Strategy, resource orchestration and e-commerce enabled social innovation in rural China. *Journal of Strategic Information Systems*, 26(1), 3–21.
- Deepthi, M. B., & Sreekantha, D. K. (2017). Application of expert systems for agricultural crop disease diagnoses—A review. 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), 222–229. <https://doi.org/10.1109/ICICCT.2017.7975192>
- FAO. (2002). *Lychee production in the Asia-Pacific region*. FAO Regional Office for Asia and the Pacific.
- FAO. (2019). *Digital technologies in agriculture and rural areas*.
- FAO. (2021). *The impact of disasters and crises on agriculture and food security*.
- Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2), 255–298.
- Fu, X., & Akter, S. (2016). The impact of mobile phone technology on agricultural extension services delivery: Evidence from India. *Journal of Development Studies*, 52(11), 1561–1576. <https://doi.org/10.1080/00220388.2016.1146700>
- Gardezi, M., & Bronson, K. (2019). Examining the social and biophysical determinants of U.S. Midwestern corn farmers' adoption of precision agriculture. *Precision Agriculture*, 21, 549–568.
- Hallau, L., Neumann, M., Klatt, B., Kleinhenz, B., Klein, T., Kuhn, C., Röhrig, M., Bauckhage, C., Kersting, K., Mahlein, A. K., Steiner, U., & Oerke, E. C. (2018). Automated identification of sugar beet diseases using smartphones. *Plant Pathology*, 67, 399–410.

- Hansen, B. G. (2015). Robotic milking-farmer experiences and adoption rate in Jæren, Norway. *Journal of Rural Studies*, 41, 109–117. <https://doi.org/10.1016/J.JRURSTUD.2015.08.004>
- Hübner, M., & Hartje, R. (2016). Are smartphones smart for economic development. *Economics Letters*, 141, 130–133. <https://doi.org/10.1016/J.ECONLET.2016.02.001>
- Jafari, Y., Koppenberg, M., Hirsch, S., & Heckelet, T. (2022). Markups and export behavior: Firm-level evidence from the French food processing industry. *American Journal of Agricultural Economics*, 1–21. <https://doi.org/10.1111/ajae.12292>
- Jenkins, A., Velandia, M., Lambert, D. M., Roberts, R. K., Larson, J. A., English, B. C., & Martin, S. W. (2011). Factors influencing the selection of precision farming information sources by cotton producers. *Agricultural and Resource Economics Review*, 40, 307–320.
- Jensen, H. G., Jacobsen, L.-B., Pedersen, S. M., & Tavella, E. (2012). Socioeconomic impact of widespread adoption of precision farming and controlled traffic systems in Denmark. *Precision Agriculture*, 13(6), 661–677. <https://doi.org/10.1007/S11119-012-9276-3>
- Jensen, R. (2007). The digital divide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *The Quarterly Journal of Economics*, 122(3), 879–924.
- Jensen, R. T. (2010). Information, efficiency, and welfare in agricultural markets. *Agricultural Economics*, 41(1), 203–216.
- Johannes, A., Picon, A., Alvarez-Gila, A., Echazarra, J., Rodriguez-Vaamonde, S., Navajas, A. D., & Ortiz-Barredo, A. (2017). Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case. *Computers and Electronics in Agriculture*, 138, 200–209. <https://doi.org/10.1016/J.COMPAG.2017.04.013>
- Kercker, M., Knierim, A., Wurbs, A., Kraus, T., & Borges, F. (2020). Experience versus expectation: Farmers' perceptions of smart farming technologies for cropping systems across Europe. *Precision Agriculture*, 21(1), 34–50. <https://doi.org/10.1007/S11119-019-09651-Z>
- Kizza, B., & Pederson, G. (2012). ICT-based market information and adoption of agricultural seed technologies: Insights from Uganda. *Telecommunications Policy*, 36(4), 253–259. <https://doi.org/10.1016/J.TELPOL.2012.01.001>
- Klerck, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS: Wageningen Journal of Life Sciences*, 90–91, 1–16. <https://doi.org/10.1016/J.NJAS.2019.100315>
- Kutter, T., Tiemann, S., Siebert, R., & Fountas, S. (2011). The role of communication and co-operation in the adoption of precision farming. *Precision Agriculture*, 12(1), 2–17. <https://doi.org/10.1007/S11119-009-9150-0>
- Laroche, C., Alwang, J., Travis, E., Barrera, V. H., & Andrade, J. M. D. (2019). Did you really get the message? using text reminders to stimulate adoption of agricultural technologies. *Journal of Development Studies*, 55(4), 548–564. <https://doi.org/10.1080/00220388.2017.1393522>
- Leng, C., Ma, W., Tang, J., & Zhu, Z. (2020). ICT adoption and income diversification among rural households in China. *Applied Economics*, 52, 1–15.
- Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors. *The Stata Journal*, 11(3), 368–385.
- Lowenberg-DeBoer, J., & Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agronomy Journal*, 111(4), 1552–1569. <https://doi.org/10.2134/AGRONJ2018.12.0779>
- Lucas, J. A. (2011). Advances in plant disease and pest management. *The Journal of Agricultural Science*, 149, 91–114. <https://doi.org/10.1017/S0021859610000997>
- Ma, W., Abdulai, A., & Goetz, R. (2017). Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, 100(2), 502–520. <https://doi.org/10.1093/ajae/aax079>
- Ma, W., Grafton, R. Q., & Renwick, A. (2020). Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research*, 20(4), 713–736. <https://doi.org/10.1007/s10660-018-9323-x>
- Ma, W., Renwick, A., Nie, P., Tang, J., & Cai, R. (2018). Off-farm work, smartphone use and household income: Evidence from rural China. *China Economic Review*, 52, 80–94. <https://doi.org/10.1016/j.chieco.2018.06.002>
- Ma, W., & Wang, X. (2020). Internet use, sustainable agricultural practices and rural incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics*, 64(4), 1087–1112. <https://doi.org/10.1111/1467-8489.12390>
- Ma, W., Zhou, X., & Liu, M. (2020). What drives farmers' willingness to adopt e-commerce in rural China? The role of Internet use. *Agribusiness*, 36(1), 159–163. <https://doi.org/10.1002/AGR.21624>
- Ma, W., & Zhu, Z. (2020). Internet use and willingness to participate in garbage classification: An investigation of Chinese residents. *Applied Economics Letters*, 28, 1–6. <https://doi.org/10.1080/13504851.2020.1781766>
- Michels, M., Facke, W., Feil, J.-H., Musshoff, O., Pigisch, J., & Krone, S. (2020). Smartphone adoption and use in agriculture: Empirical evidence from Germany. *Precision Agriculture*, 21(2), 403–425. <https://doi.org/10.1007/s11119-019-09675-5>
- Min, S., Liu, M., & Huang, J. (2020). Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *Journal of Asian Economics*, 70, 101219.

- Möhring, N., Bozzola, M., Hirsch, S., & Finger, R. (2020). Are pesticides risk decreasing? The relevance of pesticide indicator choice in empirical analysis. *Agricultural Economics*, 51(3), 429–444. <https://doi.org/10.1111/agec.12563>
- Mwololo, H. M., Nzuma, J. M., Ritho, C. N., & Aseta, A. (2019). Is the type of agricultural extension services a determinant of farm diversity? *Evidence from Kenya*, 6, 40–46.
- Nie, P., Ma, W., & Sousa-Poza, A. (2020). The relationship between smartphone use and subjective well-being in rural China. *Electronic Commerce Research*, 21, 1–27. <https://doi.org/10.1007/s10660-020-09397-1>
- Norton, G. W., & Alwang, J. (2020). Changes in agricultural extension and implications for farmer adoption of new practices. *Applied Economic Perspectives And Policy*, 42(1), 8–20. <https://doi.org/10.1002/AEPP.13008>
- Ogutu, S. O., Okello, J. J., & Otieno, D. J. (2014). Impact of information and communication technology-based market information services on smallholder farm input use and productivity: The case of Kenya. *World Development*, 64, 311–321. <https://doi.org/10.1016/j.worlddev.2014.06.011>
- Panda, C. K. (2020). Advances in application of ICT in crop pest and disease management. In C. Egbuna & B. Sawicka (Eds.), *Natural Remedies for Pest, Disease and Weed Control* (pp. 235–242). Academic Press.
- Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013). *Drivers of precision agriculture technologies adoption: A literature review*. Paper presented at the International Conference on Information and Communication Technologies.
- Pivoto, D., Barham, B., Waquil, P. D., Foguesatto, C. R., Corte, V. F. D., Zhang, D., & Talamini, E. (2019). Factors influencing the adoption of smart farming by Brazilian grain farmers. *The International Food and Agribusiness Management Review*, 22(4), 571–588. <https://doi.org/10.22434/IFAMR2018.0086>
- Pongnumkul, S., Chaovalit, P., & Surasvadi, N. (2015). Applications of smartphone-based sensors in agriculture: A systematic review of research. *Journal of Sensors*, 2015, 195308. <https://doi.org/10.1155/2015/195308>
- Rajkhowa, P., & Qaim, M. (2022). Mobile phones, off-farm employment and household income in rural India. *Journal of Agricultural Economics*, 73, 789–805. <https://doi.org/10.1111/1477-9552.12480>
- Satyanarayan, K., Jagadeeswary, V., Belakeri, P., Babu, A., & Srinivas, Y. (2018). Develop and evaluate use of mobile application for cattle farming: A new generation technology transfer for sustainable dairy production. *International Journal of Livestock Research*, 8(12), 224–232. <https://doi.org/10.5455/IJLR.20180413044608>
- StataPress. (2019). *Extended regression models reference manual*.
- Takahashi, K., Muraoka, R., & Otsuka, K. (2019). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, 51, 31–45. <https://doi.org/10.1111/agec.12539>
- Tey, Y. S., & Brindal, M. K. (2012). Factors influencing the adoption of precision agricultural technologies: A review for policy implications. *Precision Agriculture*, 13(6), 713–730. <https://doi.org/10.1007/s11119-012-9273-6>
- Tsan, M., Totapally, S., Hailu, M., & Addom, B. K. (2019). *The digitalisation of African agriculture report 2018–2019*. CTA.
- Twumasi, M. A., Jiang, Y., Asante, D., Addai, B., & Fosu, P. (2021). Internet use and farm households food and nutrition security nexus: The case of rural Ghana. *Technology in Society*, 65(2021), 101592.
- Wang, K., Zhang, S., Wang, Z., Liu, Z., & Yang, F. (2013). Mobile smart device-based vegetable disease and insect pest recognition method. *Intelligent Automation and Soft Computing*, 19(3), 263–273. <https://doi.org/10.1080/10798587.2013.823783>
- WorldBank. (2016). *World development report 2016: Digital dividends*.
- Zhang, Y., Wang, L., & Duan, Y. (2016). Agricultural information dissemination using ICTs: A review and analysis of information dissemination models in China. *Information Processing in Agriculture*, 3(1), 17–29. <https://doi.org/10.1016/j.inpa.2015.11.002>
- Zhao, Q., Pan, Y., & Xia, X. (2021). Internet can do help in the reduction of pesticide use by farmers: Evidence from rural China. *Environmental Science and Pollution Research*, 28(6), 7068–7075.
- Zheng, H., & Ma, W. (2021). Smartphone-based information acquisition and wheat farm performance: Insights from a doubly robust IPWRA estimator. *Electronic Commerce Research*, 1–26. <https://doi.org/10.1007/s10660-021-09481-0>
- Zhu, Z., Ma, W., & Leng, C. (2021). ICT adoption and tourism consumption among rural residents in China. *Tourism Economics*. <https://doi.org/10.1177/13548166211000478>

AUTHOR BIOGRAPHIES

Yi Cai is an assistant professor in the College of Economics and Management at South China Agricultural University. Dr. Yi Cai earned his Ph.D. degree from Huazhong Agriculture University. His major fields of study are Information and Communication Technology (ICT) development for rural areas, rural urbanization, and poverty-related issues.

Wene Qi is an associate professor in the College of Economics and Management at South China Agricultural University. She has a Ph.D. in math from Zhengzhou University. Her research focuses on agribusiness.

Famin Yi is a professor in the College of Economics and Management at South China Agricultural University. Prof. Famin Yi earned his Ph.D. degree from Renmin University. His research areas are digital agriculture and poverty alleviation.

How to cite this article: Cai, Y., Qi, W., & Yi, F. (2022). Smartphone use and willingness to adopt digital pest and disease management: Evidence from litchi growers in rural China. *Agribusiness*, 1–17.
<https://doi.org/10.1002/agr.21766>

APPENDIX A

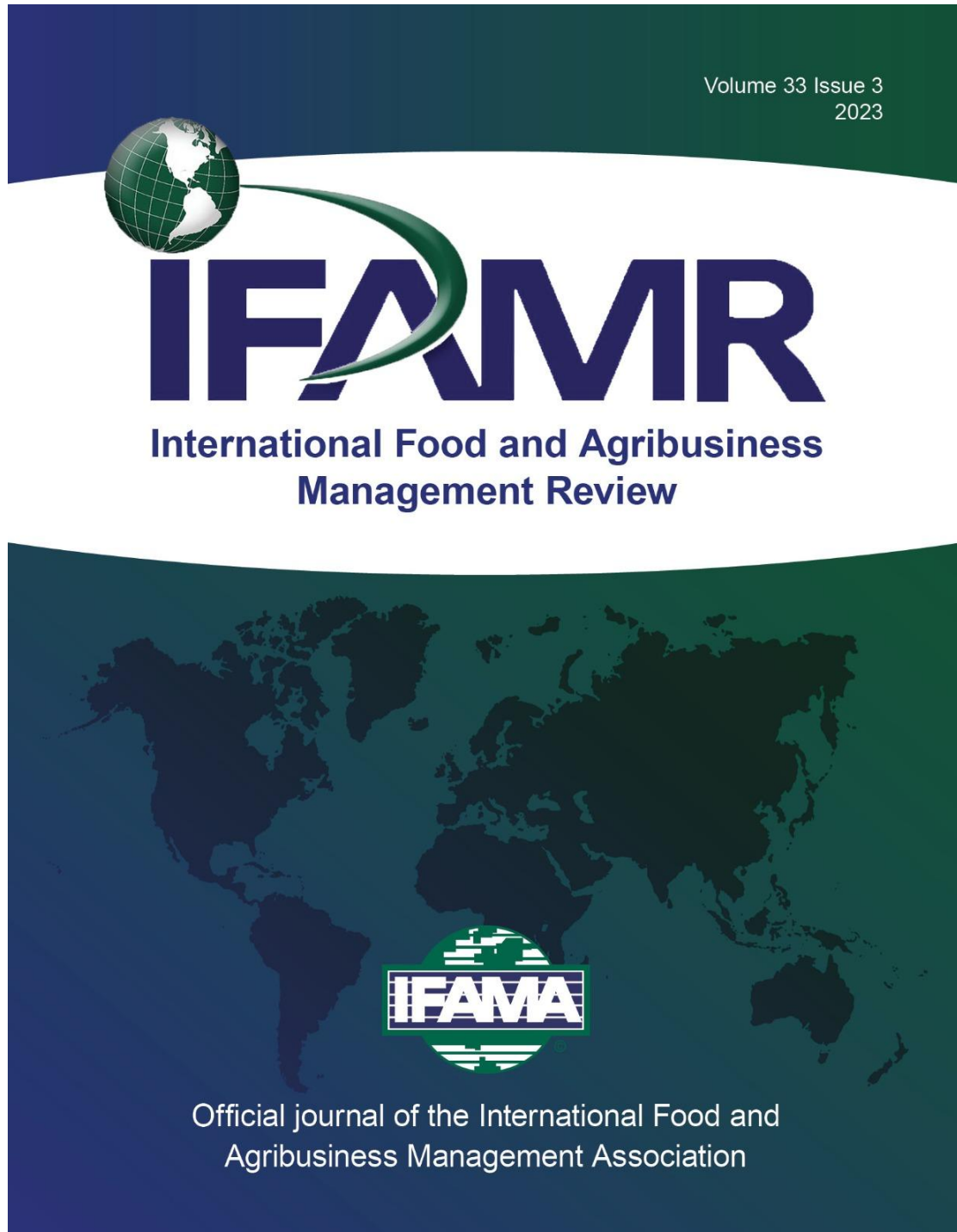
See Table A1.

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





Wageningen Academic
Publishers

Moving ahead and excellent to the future
More information

Sign in | Register | Institutional Access

Home | Books | Journals | Authors | Libraries | Lecturers | Conferences | News

Advised search

Home > International Food and Agribusiness Management Review > List of Issues > Vol. 25, No. 4

About | Issues | Editorial | Pricing | Submissions

Vol. 25, No. 4, 2022

☐ Select All For selected items:

CASE STUDY

☐ Sustainable value creation – a firm case on business model innovation
Prodi Pertiwi, Vera Salwa, Pin-Asden Lajenda
25(4): pp. 543–564
<https://doi.org/10.22434/IFAMR2021.0114>
Keywords: agribusiness, business model, strategy, competitiveness, management
Abstract | References | Full-text (312 KB)

RESEARCH ARTICLE

☐ Students' perception towards IFAMA agribusiness case study competition: do culture, discipline, and training experience matter?
Zhangxi Zhu, Chung-Chen Tsai, Yie Wang
25(4): pp. 555–570
<https://doi.org/10.22434/IFAMR2021.0141>
Keywords: case study competition, agribusiness, culture, discipline, training experience
Abstract | References | Full-text (317 KB) | Supplemental Material

☐ Information interventions and health promotion behavior: evidence from China after cadmium rice events
Jiehong Zhou, Jing Zhang, Li Zhou
25(4): pp. 571–586
<https://doi.org/10.22434/IFAMR2021.0394>
Keywords: information interventions, food safety, consumer behavior, health promotion, China
Abstract | References | Full-text (321 KB) | Supplemental Material

☐ Impacts of work attitude of outsourcing services on food losses: evidence from rice harvest in China
Jie Gu, Daimi Ajima, Leping Wu, Mitsuyoshi Ando
25(4): pp. 587–596
<https://doi.org/10.22434/IFAMR2021.0104>
Keywords: farm scale, food losses, moral hazard, outsourcing services, rice harvest
Abstract | References | Full-text (375 KB)

☐ Why can't the supply chain keep up with organic bakery product demand? Understanding miller, distributor, and baker organic wheat quality perceptions and needs
Isabella Dugoni, Kynia R. Carter
25(4): pp. 601–617
<https://doi.org/10.22434/IFAMR2021.0136>
Keywords: grain marketing, organic, quality, supply chains, wheat
Abstract | References | Full-text (333 KB)

☐ Broiler production systems in Ghana: economics and the impact of frozen chicken imports
Osei Chibinda, Abenahed Isah Ahmed, Fatah Frode, Christine Wilezi
25(4): pp. 619–624
<https://doi.org/10.22434/IFAMR2021.0142>
Keywords: broilers, chickens, imports, production systems
Abstract | References | Full-text (512 KB)

☐ Risk and return of heterogeneous farmland locations and qualities
Ashraf Hossain, Ahmed Langemeier
25(4): pp. 635–660
<https://doi.org/10.22434/IFAMR2021.0061>
Keywords: farmland, farmland quality, minimum-variance (min-var) portfolio, reward-to-risk ratio, capital asset pricing model (CAPM)
Abstract | References | Full-text (462 KB) | Supplemental Material

☐ Exploring multiple drivers of cooperative governance: a paired case comparison of vegetable growing cooperatives in the UK and China
Dan Liang, Han Dong, Agha R. Baki, Ibrahim Ali, Fu Jie
25(4): pp. 651–670
<https://doi.org/10.22434/IFAMR2021.0175>
Keywords: farmer cooperative, governance attitude, member heterogeneity, legislation, culture
Abstract | References | Full-text (367 KB)

☐ Impact of smartphone use on production outsourcing: evidence from itchi farming in southern China
Yi Gu, Yuchang Sun, Wen Qi, Fanchi Ji
25(4): pp. 671–682
<https://doi.org/10.22434/IFAMR2021.0166>
Keywords: smartphones, agricultural production outsourcing, genetic modification

International Food and Agribusiness Management Review



Online ISSN: 1559-2448

Tools | Most Read | Most Cited

Site Tools

Sign up for a alert
[Alert](#) (What is this?)

OPEN ACCESS



International Food and Agribusiness Management Review
Please cite this article as 'in press'; DOI: 10.22434/IFAMR2021.0155

Received: 30 November 2021 / Accepted: 28 January 2022

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

RESEARCH ARTICLE

Yi Cai^{a,b,c}, Yucheng Sun^d, Wene Qi[Ⓔ] and Famin Yi^{f,g}

^aAssistant Professor, ^cAssociate Professor, ^fProfessor, College of Economics and Management, South China Agricultural University, 483 Wushan Road, Guangzhou, 510640, China P.R.

^bAssistant Professor, Research Center for Green Development of Agriculture, South China Agricultural University, Guangzhou, 510640, China P.R.

^eAssistant Professor, ^gProfessor, Digital Countryside Research Institute, South China Agricultural University, Guangzhou, 510640, China P.R.

^dPhD, Lingnan College, Sun Yat-Sen University, Guangzhou, 510275, China P.R.

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

[Ⓔ]Corresponding author: qiwene@scau.edu.cn

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.¹ In the same year, the Seventh National Population Census of China revealed that the urbanization rate reached 63.89%.² 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.

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

² Main data from the Seventh National Population Census of China: 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 ¹
Labor-intensive tasks		
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)
Technology-intensive tasks		
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)

¹ 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 2020.³ 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.

³ Summary report of the China Internet Network Information Center: 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) ¹
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 ²)	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)

¹ SD = standard deviation.

² 1 USD = 6.36 Yuan.

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

	Users ¹	Nonusers ¹	Mean difference ^{2,3}
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	

¹ Mean and standard deviation (in parentheses).

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

³ ** 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.¹

	Before matching					After matching			
	Treatment mean	Control mean	SMD ²	D ³	P-value ⁴	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

¹ Yulin is the reference city.² SMD = standardized mean difference.³ The D-statistic is the maximum difference in the empirical quantile-quantile plot.⁴ 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,⁴ 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.

⁴ 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) ^{1,2}
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)

¹ SE = robust Abadie-Imbens standard errors.

² *, ** 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.

Acknowledgements

This study was supported by China Agriculture Research System of MOF and MARA (CARS-34-17), the Youth Project of Guangdong Provincial Department of Education (2020WQNCX006), and the Social Science Fund of Guangdong (GD21YYJ06), and the National Social Science Fund of China (19BGL256).

Conflict of interest

The authors declare that they have no conflict of interest.

References

- Aker, J.C. 2011. Dial 'A' for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics* 42(6): 631-647.
- Aker, J.C., I. Ghosh and J. Burrell. 2016. The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics* 47(S1): 35-48.
- Austin, P.C. 2008. A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003. *Statistics in Medicine* 27(12): 2037-2049.
- Beuermann, D.W. 2015. *Information and communications technology, agricultural profitability and child labor in rural Peru*. IDB Working Paper Series 454. Inter-American Development Bank (IDB), Washington, DC, USA.
- Cai, Y., W. Qi and F. Yi. 2022. Mobile internet adoption and technology adoption extensity: evidence from litchi growers in southern China. *China Agricultural Economic Review* 14(1): 106-121.
- Campenhout, B.V., D.J. Spielman and E. Lecoutere. 2021. Information and communication technologies to provide agricultural advice to smallholder farmers: experimental evidence from Uganda. *American Journal of Agricultural Economics* 103(1): 317-337.
- Cochran, W.G. and D.B. Rubin. 1974. Controlling bias in observational studies: a review. *Journal of Statistics, Series A* 35(4): 417-446.
- Deng, X., D.-D. Xu, M. Zeng and Y. Qi. 2020. Does outsourcing affect agricultural productivity of farmer households? Evidence from China. *China Agricultural Economic Review* 12: 673-688.
- Deng, X., D. Xu, M. Zeng and Y. Qi. 2019. Does internet use help reduce rural cropland abandonment? Evidence from China. *Land Use Policy* 89: 104243.
- Diamond, A. and J.S. Sekhon. 2013. Genetic matching for estimating causal effects: a general multivariate matching method for achieving balance in observational studies. *The Review of Economics and Statistics* 95(3): 932-945.
- Frey, S.M. 2014. The economic burden of schizophrenia in Germany: a population-based retrospective cohort study using genetic matching. *European Psychiatry* 29: 479-489.
- Jensen, R.T. 2010. Information, efficiency, and welfare in agricultural markets. *Agricultural Economics* 41(1): 203-216.
- Ji, C., H. Guo, S. Jin and J. Yang. 2017. Outsourcing agricultural production: evidence from rice farmers in Zhejiang Province. *PLoS ONE* 12(1): e0170861.
- Kiiza, B. and G. Pederson. 2012. ICT-based market information and adoption of agricultural seed technologies: insights from Uganda. *Telecommunications Policy* 36(4): 253-259.
- Larochelle, C., J. Alwang, E. Travis, V.H. Barrera and J.M.D. Andrade. 2019. Did you really get the message? Using text reminders to stimulate adoption of agricultural technologies. *Journal of Development Studies* 55(4): 548-564.
- Leng, C., W. Ma, J. Tang and Z. Zhu. 2020. ICT adoption and income diversification among rural households in China. *Applied Economics* 52(33): 3614-3628.
- Liu, Y., Y. Liu, Y. Chen and H. Long. 2010. The process and driving forces of rural hollowing in China under rapid urbanization. *Journal of Geographical Sciences* 20(6): 876-888.
- Ma, W., R.Q. Grafton and A. Renwick. 2018. Smartphone use and income growth in rural China: empirical results and policy implications. *Electronic Commerce Research* 20(4): 713-736.
- Ma, W., P. Nie, P. Zhang and A. Renwick. 2020a. Impact of Internet use on economic well-being of rural households: evidence from China. *Review of Development Economics* 24(2): 503-523.
- Ma, W. and X. Wang. 2020. Internet use, sustainable agricultural practices and rural incomes: evidence from China. *Australian Journal of Agricultural and Resource Economics* 64(4): 1087-1112.
- Ma, W., X. Zhou and M. Liu. 2020b. What drives farmers' willingness to adopt e-commerce in rural China? The role of internet use. *Agribusiness* 36(1): 159-163.
- Mi, Q., X. Li and J. Gao. 2020. How to improve the welfare of smallholders through agricultural production outsourcing: evidence from cotton farmers in Xinjiang, Northwest China. *Journal of Cleaner Production* 256: 120636.

- Min, S., M. Liu and J. Huang. 2020. Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *Journal of Asian Economics* 70: 101219.
- Nie, P., W. Ma and A. Sousa-Poza. 2020. The relationship between smartphone use and subjective well-being in rural China. *Electronic Commerce Research* 21: 983-1009.
- Ogutu, S.O., J.J. Okello and D.J. Otieno. 2014. Impact of information and communication technology-based market information services on smallholder farm input use and productivity: the case of Kenya. *World Development* 64: 311-321.
- Okello, J.J., O.K. Kirui and Z.M. Gitonga. 2020. Participation in ICT-based market information projects, smallholder farmers' commercialisation, and agricultural income effects: findings from Kenya. *Development in Practice* 30(8): 1043-1057.
- Rosenbaum, P.R. and D.B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1): 41-55.
- Sekhon, J.S. 2011. Multivariate and propensity score matching software with automated balance optimization: the matching package for R. *Journal of Statistical Software* 42(7): 1-52.
- Sekhon, J.S. and R.D. Grieve. 2012. A matching method for improving covariate balance in cost-effectiveness analyses. *Health Economics* 21(6): 695-714.
- Shiferaw, B., T. Kebede, M. Kassie and M. Fisher. 2015. Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints. *Agricultural Economics* 46(4): 475-488.
- Su, S., Z. Jiang, Q. Zhang and Y. Zhang. 2011. Transformation of agricultural landscapes under rapid urbanization: a threat to sustainability in Hang-Jia-Hu region, China. *Applied Geography* 31(2): 439-449.
- Sun, D., M. Rickaille and Z. Xu. 2018. Determinants and impacts of outsourcing pest and disease management. *China Agricultural Economic Review* 10(3): 443-461.
- Twumasi, M.A., Y. Jiang, D. Asante, B. Addai and P. Fosu. 2021. Internet use and farm households food and nutrition security nexus: the case of rural Ghana. *Technology in Society* 65: 101592.
- Wang, J., K.Z. Chen, S.D. Gupta and Z. Huang. 2015. Is small still beautiful? A comparative study of rice farm size and productivity in China and India. *China Agricultural Economic Review* 7(3): 484-509.
- Zhang, Q., B. Yan and X. Huo. 2018. What are the effects of participation in production outsourcing? Evidence from Chinese apple farmers. *Sustainability* 10(12): 4525.
- Zhang, X., J. Yang and R. Thomas. 2017. Mechanization outsourcing clusters and division of labor in Chinese agriculture. *China Economic Review* 43(1415): 184-195.
- Zhao, Q., Y. Pan and X. Xia. 2021. Internet can do help in the reduction of pesticide use by farmers: evidence from rural China. *Environmental Science and Pollution Research* 28(6): 2063-2073.
- Zheng, H. and W. Ma. 2021a. Impact of ICT adoption on cosmetic expenditure of Chinese residents: an exploration accounting for urban-rural differentials. *Applied Economics Letters*. <https://doi.org/10.1080/13504851.2021.1927953>
- Zheng, H. and W. Ma. 2021b. Smartphone-based information acquisition and wheat farm performance: insights from a doubly robust IPWRA estimator. *Electronic Commerce Research*. <https://doi.org/10.1007/s10660-021-09481-0>
- Zheng, H., W. Ma, F. Wang and G.-C. Li. 2021. Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy* 105: 102044.
- Zhu, X., R.-F. Hu, C. Zhang and G. Shi. 2021a. Does internet use improve technical efficiency? Evidence from apple production in China. *Technological Forecasting and Social Change* 166: 120662.
- Zhu, Z., W. Ma and C. Leng. 2021b. ICT adoption and tourism consumption among rural residents in China. *Tourism Economics*. <https://doi.org/10.1177/13548166211000478>
- Zhu, Z., W. Ma and C. Leng. 2020a. ICT adoption, individual income and psychological health of rural farmers in China. *Applied Research in Quality of Life* 17: 71-91.
- Zhu, Z., W. Ma, A. Sousa-Poza and C. Leng. 2020b. The effect of internet usage on perceptions of social fairness: Evidence from rural China. *China Economic Review* 62: 101508.

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



Access and authentication: Please visit our page:
Close

emerald insight
Discover journals, books & case studies

Browse our content Publish with us Register for a profile Log in

Enter your search or article title
Advanced search

Home / Journals / China Agricultural Economic Review / Volume 10 Issue 1

China Agricultural Economic Review: Volume 10 Issue 1

Subject: Economics - Agricultural environmental economics - Agricultural biotechnology

Submit or view all authors details 2,102 hits

Table of contents

Evolution of the rural social security system in a large country over 35 years: Institutional transformations and the Chinese experience
Xuan xian, Mingqiang Lin
This paper aims to review the institutional evolution of China's rural social security system in the past 35 years, focusing on major policy transformations of the rural social...

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Major storage losses and its main determinants in China
Wang Zhong, Li Lu, Dong Huang, Xuan xian, Liang Xu, Junfeng Zhu
The purpose of this study was to estimate or infer major storage losses and to empirically analyse the main determinants of major storage losses in China.

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Are there dynamic productivity gains from agricultural trade?
David Martin
The primary purpose of this paper is to take an in-depth look at the question of whether liberating trade in agriculture can generate dynamic productivity gains comparable to...

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Do producers respond to quality information disclosure? The HACCP certification in meat industry
Jiahong Zhou, Xuejin Yu, Wang, Qiao Liang
Food systems are characterized by asymmetric information between suppliers and consumers, which causes inefficiency of market and food safety risks. This paper studies how the...

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Digital financial inclusion and vulnerability to poverty: evidence from Chinese rural households
Xuehui Wang, Yang Yu
Digital finance has the transformative power to make financial inclusion. However, evidence on the relationship between digital finance and poverty reduction remains limited...

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Interactive relationship between non-farm employment and mechanization service expenditure in rural China
Wangjun Zhang, Wanglin Ma, Yanfeng Guo, Baoxin Zhou
The purpose of this study is to investigate the interactive relationship between non-farm employment and mechanization service expenditure...

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

Mobile Internet adoption and technology adoption intensity: evidence from fifth growers in western China
M Gu, Huijie Qi, Kaimin Yi
The purpose of this study is to examine the effects of mobile internet adoption on technology adoption intensity.

PDF icon
PDF icon
PDF icon
PDF icon
PDF icon
PDF icon

China Agricultural Economic Review

ISSN: 1750-1329

Online dates, start - end: 2023

Copyright holder: Emerald Publishing Limited

Open Access: Full Text

Editors:

- Dr Fu Qiu
- Dr Jiahong Huang
- Dr Wenhui Chen
- Dr Wenhui Chen
- Prof David Martin
- Prof David Martin
- Prof Holly Wang

Further information:

- About the journal
- For more information
- Contact us
- Write for this journal

CAER
14,1

106

Received 4 November 2020
Revised 4 February 2021
26 March 2021
24 June 2021
Accepted 9 August 2021

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

Yi Cai, Wene Qi and Famin Yi

*College of Economics and Management, Digital Countryside Research Institute,
South China Agricultural University, Guangzhou, China*

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

This study was supported by China Agriculture Research System of MOF and MARA (CARS-34-17), the special funds for the development of high level universities (4700-220140), the Youth Project of Guangdong Provincial Department of Education (Research on the formation and cultivation mechanism of farmers' digital capital), and the National Social Science Fund of China (19BGL256).

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.



China Agricultural Economic
Review
Vol. 14 No. 1, 2022
pp. 106-121
© Emerald Publishing Limited
1756-137X
DOI 10.1108/CAER-11-2020-0260

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 Bahigwa, 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.

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

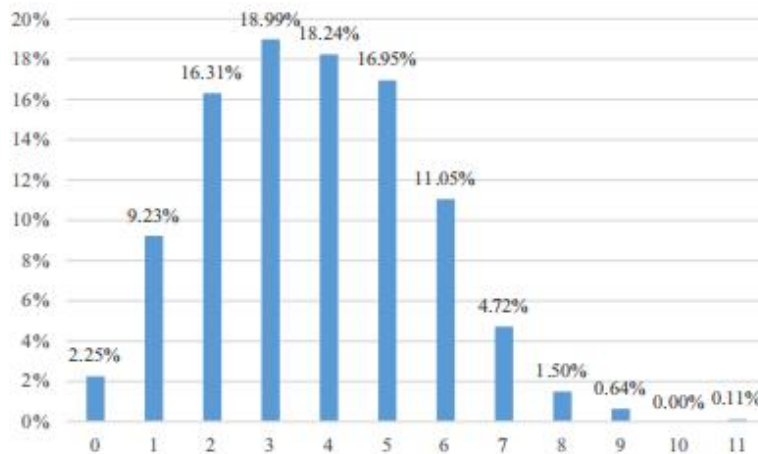
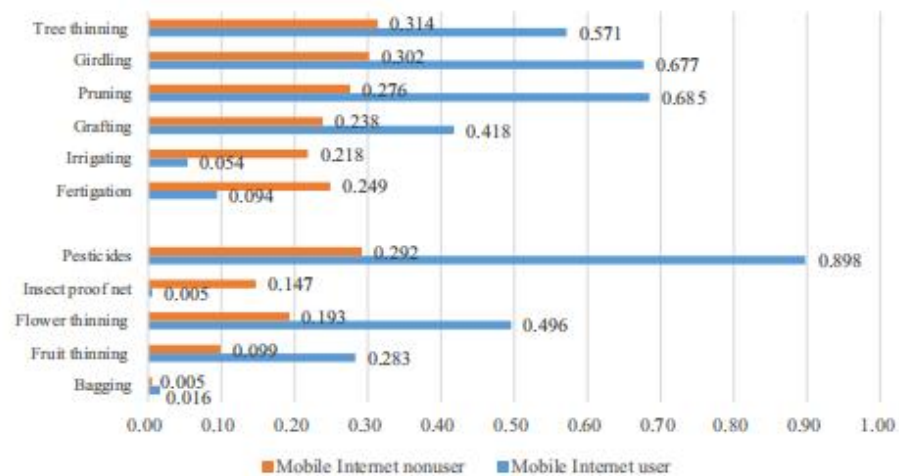


Figure 1.
The distribution of
technology adoption
extensity

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; α_i is a vector of parameters to be estimated; and μ_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.

The effects of mobile Internet adoption

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 ρ 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.

115

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)
ρ	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.

The effects of
mobile Internet
adoption

117

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 ρ 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 adoption (Coef.)	Capital-intensive technology adoption extensity (IRRs)	Mobile Internet adoption (Coef.)	Labor-intensive technology adoption extensity (IRRs)
Mobile Internet 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 farming 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 membership	0.202 (0.145)	1.010 (0.058)	0.201 (0.143)	0.939 (0.037)
Cooperatives 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)
ρ	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.

References

- Aker, J.C. (2011), "Dial 'A' for agriculture: a review of information and communication technologies for agricultural extension in developing countries", *Agricultural Economics*, Vol. 42, pp. 631-647.
- Aker, J.C., Ghosh, I. and Burrell, J. (2016), "The promise (and pitfalls) of ICT for agriculture initiatives", *Agricultural Economics*, Vol. 47, pp. 35-48.
- Baumüller, H. (2012), *Facilitating Agricultural Technology Adoption Among the Poor: the Role of Service Delivery through Mobile Phones*, ZEF Working Paper Series 93, doi: [10.2139/ssrn.2237987](https://doi.org/10.2139/ssrn.2237987).
- Baumüller, J. (2003), *World Agriculture: Towards 2015/2030, An Fao Perspective*, Earthscan, London.
- Cameron, A.C. and Trivedi, P.K. (2009), *Microeconometrics Using Stata*, Stata Press, College Station, TX.
- Chang, H.H. and Just, D.R. (2009), "Internet access and farm household income – empirical evidence using a semi-parametric assessment in Taiwan", *Journal of Agricultural Economics*, Vol. 60, pp. 348-366.
- Dridi, C. and Khraief, N. (2011), "The diffusion of new technology: adoption subsidies, spillovers, and transaction costs", *Economics Bulletin*, Vol. 31, pp. 771-781.
- Fu, X. and Akter, S. (2016), "The impact of mobile phone technology on agricultural extension services delivery: evidence from India", *Journal of Development Studies*, Vol. 52, pp. 1561-1576.
- Gbadegesin, T.K. and Popoola, L. (2020), "Effectiveness of collective action in reducing transaction cost for smallholder paddy farmers in Tanzania", *African Journal of Economic and Sustainable Development*, Vol. 7, pp. 391-404.
- Goldfarb, A. and Prince, J. (2008), "Internet adoption and usage patterns are different: implications for the digital divide", *Information Economics and Policy*, Vol. 20, pp. 2-15.
- Janvry, Ad and Sadoulet, E. (2002), "World poverty and the role of agricultural technology: direct and indirect effects", *Journal of Development Studies*, Vol. 38, pp. 1-26.
- Jensen, R. (2007), "The digital divide: information (technology), market performance, and welfare in the South Indian fisheries sector", *The Quarterly Journal of Economics*, Vol. 122, pp. 879-924.
- Jensen, R.T. (2010), "Information, efficiency, and welfare in agricultural markets", *Agricultural Economics*, Vol. 41, pp. 203-216.
- Khanal, A.R. and Mishra, A.K. (2016), "Financial performance of small farm business households: the role of internet", *China Agricultural Economic Review*, Vol. 8, pp. 553-571.
- Kiiza, B. and Pederson, G. (2012), "ICT-based market information and adoption of agricultural seed technologies: insights from Uganda", *Telecommunications Policy*, Vol. 36, pp. 253-259.
- Leng, C., Ma, W., Tang, J. Zhu, Z. (2020), "ICT adoption and income diversification among rural households in China", *Applied Economics*, pp. 1-15.

- Ma, W. and Wang, X. (2020), "Internet use, sustainable agricultural practices and rural incomes: evidence from China*", *Australian Journal of Agricultural and Resource Economics*.
- Magrini, E. and Vigani, M. (2016), "Technology adoption and the multiple dimensions of food security: the case of maize in Tanzania", *Food Security*, Vol. 8, pp. 707-726.
- Martínez-Domínguez, M. and Mora-Rivera, J. (2020), "Internet adoption and usage patterns in rural Mexico", *Technology in Society*, Vol. 60.
- Melguizo, T., Sanchez, F. and Velasco, T. (2016), "Credit for low-income students and access to and academic performance in higher education in Colombia: a regression discontinuity approach", *World Development*, Vol. 80, pp. 61-77.
- Mendola, M. (2007), "Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh", *Food Policy*, Vol. 32, pp. 372-393.
- Muzari, W., Gatsi, W. and Muvhunzi, S. (2012), "The impacts of technology adoption on smallholder agricultural productivity in sub-saharan africa: a review", *Journal of Sustainable Development*, Vol. 5.
- Mwangi, M. and Kariuki, S. (2015), "Factors determining adoption of new agricultural technology by smallholder farmers in developing countries", *Journal of Economics and Sustainable Development*, Vol. 6, pp. 208-216.
- Odozi, J.C. and Omonona, B.T. (2013), "Socio-economic determinants of irrigation technology adoption in the management of climate risk in Nigeria", *Journal of Agriculture Forestry and the Social Sciences*, Vol. 11, pp. 1-15.
- Ogutu, S.O., Okello, J.J. and Otieno, D.J. (2014), "Impact of information and communication technology-based market information services on smallholder farm input use and productivity: the case of Kenya", *World Development*, Vol. 64, pp. 311-321.
- Pan, Y., Smith, S.C. and Sulaiman, M. (2018), "Agricultural extension and technology adoption for food security: evidence from Uganda", *American Journal of Agricultural Economics*, Vol. 100, pp. 1012-1031.
- Penard, T., Poussing, N., Mukoko, B. and Piaptie, G.B.T. (2015), "Internet adoption and usage patterns in Africa: evidence from Cameroon", *Technology in Society*, Vol. 42, pp. 71-80.
- Schultz, T.W. (1964), "Transforming Traditional agriculture (studies in comparative economics)", *Economics*, Vol. 37, pp. 47-61.
- Stata (2019), *STATA Treatment-Effects Reference Manual: Potential Outcomes/Counterfactual Outcomes-Release*, StataCorp LLC, College Station, TX, Vol. 16.
- Sunding, D. and Zilberman, D. (2001), "The agricultural innovation process: research and technology adoption in a changing agricultural sector", *Handbook of Agricultural Economics*, Vol. 1, pp. 207-261.
- Tadesse, G. and Bahiigwa, G. (2015), "Mobile phones and farmers' marketing decisions in Ethiopia", *World Development*, Vol. 68, pp. 296-307.
- WorldBank (2016), *World Development Report 2016: Digital Dividends*, World Bank, Washington, DC.
- Yang, L. and Zhang, Y. (2020), "Digital financial inclusion and sustainable growth of small and micro enterprises—evidence based on China's new third board market listed companies", *Sustainability*, Vol. 12.
- Zhang, S., Sun, Z., Ma, W. and Valentinov, V. (2019), "The effect of cooperative membership on agricultural technology adoption in Sichuan, China", *China Economic Review*, p. 101334.
- Zhang, Y., Wang, L. and Duan, Y. (2016), "Agricultural information dissemination using ICTs: a review and analysis of information dissemination models in China", *Information Processing in Agriculture*, Vol. 3, pp. 17-29.

Corresponding author

Wene Qi can be contacted at: qiwene@scau.edu.cn

3. 以通讯作者发表本专业论文情况

3. 1. E-commerce participation, digital finance and farmers' income



Access and authentication: Please visit our page.
Close

emerald insight
Browse journals, books & e-conferences
Browse our content Publish with us Register for a profile Log in

Enter your search terms here
Advanced search

Home / Journals / China Agricultural Economic Review / Volume 15 Issue 4

China Agricultural Economic Review Volume 15 Issue 4

Subject: Economics / Agricultural environmental economics / Agricultural finance/policy

Subscribe to table of contents alerts 30 In All text

Table of contents

Leveraging genetic data for predicting consumer choices of antibiotic products

Chen Zhu, Timothy Beatty, Qian Zhao, Wei Li, Qian Chen

Food choices profoundly affect one's dietary, nutritional and health outcomes. Using genetic leverage as a cost study, the authors assess the potential of genetic data in...

ARTICLE
PDF (1.4 MB)
Purchase article

CONTENTS
PDF

The impact of digital economy on green development of agriculture and its spatial spillover effect

Mingpeng Wang, Xiangjie Fan, J. Wang

By discussing the spatial spillover effect and regional heterogeneity of digital economy and green agricultural development level, this paper aims to provide countermeasures and...

ARTICLE
PDF (270 KB)
Purchase article

CONTENTS
PDF

Loss of organic cattle to the conventional value chain is, indeed, what are the economic and environmental impacts?

Yanjin

This paper aims to quantify the loss for leakage of organic cattle to conventional value chain in terms of economic and environmental impacts.

ARTICLE
PDF (738)
Purchase article

CONTENTS
PDF

How does platform certification affect the marketing performance of sellers in food e-commerce? Evidence from reputation mechanisms

Huifan, Shunhan Ju, Qianrong Wu, Xuefei Song

Platform certification constitutes an effective tool for managing the food products concerning food e-commerce. This work aims to evaluate the market effect of platform...

ARTICLE
PDF (320 KB)
Purchase article

CONTENTS
PDF

Assessing the role of institutional effectiveness on carbon sequestration: the case of China's nature reserve policy

Huayan Chen, Jiao Chen, Dai Kaimo, Kun Hong, Qian Zhong

Carbon storage is protected land is a potential climate stabilization strategy. It is increasingly being recognized as an economic means of mitigating business carbon risk...

ARTICLE
PDF (377 KB)
Purchase article

CONTENTS
PDF

Can internet adoption promote the productivity of firms in China: evidence from a longitudinal study

Dong Zhou, Wenxin Wang

This paper aims to conduct research to assess the impact of Internet adoption on the productivity of firms in China using Q data.

ARTICLE
PDF (374 KB)
Purchase article

CONTENTS
PDF

The effect of human educational capital on health-related quality of life among migrant workers in China: evidence from the 2017 China Migrants Dynamic Survey

Huang Chen, Chen-Hong Chen, Wang Jin, Songgang Wang, Lijun Qin

This paper employs nationwide, large-scale field survey data to provide the first empirical evidence on the impact of human educational capital on the migration of health...

ARTICLE
PDF (362 KB)
Purchase article

CONTENTS
PDF

E-commerce participation, digital finance and farmers' income

Farah N. Ullah Khan, Farhatun Nisa, N. Cai

It is imperative to achieve sustainable growth in farmers' welfare to reduce poverty alleviation efforts and achieve rural revitalization goals. This research investigated the...

ARTICLE
PDF (3.1 MB)
Purchase article

CONTENTS
PDF

China Agricultural Economic Review

ISSN 1756-1376

Online ISSN, print + web: 2024

Copyright holder: Emerald Publishing Limited

Open Access: Hybrid

Editors:

- Dr Fu Qin
- Dr Jiamin Huang
- Dr Kevin Z. Chen
- Dr Weiming Sun
- Prof Daniel Swanson
- Prof Han Yin
- Prof Jody Wang

Further information:

- About the journal
- Purchase information
- Editorial board
- Write for this journal

E-commerce participation, digital finance and farmers' income

E-commerce participation

Famin Yi and Lihao Yao

College of Economics and Management, South China Agricultural University, Guangzhou, China

Yucheng Sun

Lingnan College, Sun Yat-Sen University, Guangzhou, China, and

Yi Cai

College of Economics and Management, South China Agricultural University, Guangzhou, China

Received 17 March 2023

Revised 7 July 2023

4 September 2023

Accepted 21 September 2023

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,



Financial support: This work was supported by the National Social Science Fund of China (19BGL256) and the Social Science Fund of Guangdong (GD21YYJ06).

Disclosure statement: No potential conflict of interest was reported by the author.

China Agricultural Economic Review
© Emerald Publishing Limited
1756-137X
DOI 10.1108/CAER-03-2023-0053

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/ 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>Age²</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; 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 ^a	2.012	1.178	1	5

Note(s): ^aRisk 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); α_p is a provincial-fixed effect used to control for some provincial-level differences that may impact the income of rural households; δ_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 β_1 and β_2 . If β_1 is positive and significant but β_2 is not significant, it indicates a single linear relationship between e-commerce participation and the income of farmer households. However, if β_1 is positive and significant, but β_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 $Y_{i,p,t}$, $\text{Employ}_{i,p,t}$, $\text{Employ}_{i,p,t}^2$, $X_{i,p,t}$, $X_{p,t}$, α_p , δ_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 β_4 . Generally, if β_4 is positive, the

moderating effect of digital finance will flatten the inverted U-shaped curve; if β_4 is negative, the moderating effect will make the curve steeper. Therefore, β_4 is the primary coefficient of interest. However, this does not imply that β_1 , β_2 and β_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 β_3 and β_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* (0.0200)	0.0402* (0.0221)	0.0398* (0.0160)	0.1725*** (0.0154) -0.0223*** (0.0006)	0.1621*** (0.0134) -0.0002*** (0.0006)	0.1119*** (0.0100) -0.0016*** (0.0006) 0.0072 (0.0123) -0.0068 (0.0116) 0.0115 (0.0067) 0.0366 (0.0035) 0.3676*** (0.0002) 0.3009*** (0.0476) -0.0324** (0.0140) -1.2011*** (0.1181) -0.3535*** (0.0908) -0.1049 (0.5324) -8.6505*** (2.4822) -0.1147 (0.1324) 0.0088 (0.0066) -1.4928 (1.3332)
<i>Employ</i> ²						
<i>Age</i>			0.0069 (0.0122)			
<i>Age</i> ²			-0.0077 (0.0115)			
<i>Gender</i>			0.0128 (0.0663)			
<i>Married</i>			0.0482 (0.0632)			
<i>Health</i>			0.2677** (0.0900)			
<i>Edu</i>			0.2044** (0.0476)			
<i>Family size</i>			-0.0327* (0.0140)			
<i>Child</i>			-1.2097*** (0.1181)			
<i>Clap</i>			-0.3600** (0.0908)			
<i>Pro_jobgdp</i>			-0.1120 (0.5319)			
<i>Pro_urban</i>			-8.6758*** (2.4758)			
<i>Pro_jobless</i>			-0.1218 (0.1322)			
<i>Pro_phone</i>			0.0087 (0.0066)			
<i>Pro_consum</i>			-1.6289 (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</i> ² _{adj}	0.0273	0.0348	0.0576	0.0286	0.0360	0.0362
<i>AIC</i>	31.004	30.940	30.576	30.994	30.931	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 β_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* (0.2546)	0.4804* (0.2531)	0.4176* (0.2510)	0.3980* (0.2386)
<i>Employ</i> ²	-0.0188*** (0.0066)	-0.0174*** (0.0066)	-0.0156** (0.0066)	-0.0127** (0.0064)
<i>Employ</i> × <i>DFI</i>	-0.0897 (0.0985)	-0.0969 (0.0963)	-0.0757 (0.0951)	-0.0917 (0.0897)
<i>Employ</i> ² × <i>DFI</i>	0.0049 (0.0022)	0.0046 (0.0022)	0.0040 (0.0022)	0.0035 (0.0021)
<i>DFI</i>	0.2975*** (0.0492)	0.2136*** (0.0427)	0.4469 (0.4501)	0.0764 (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> ² _{adj}	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

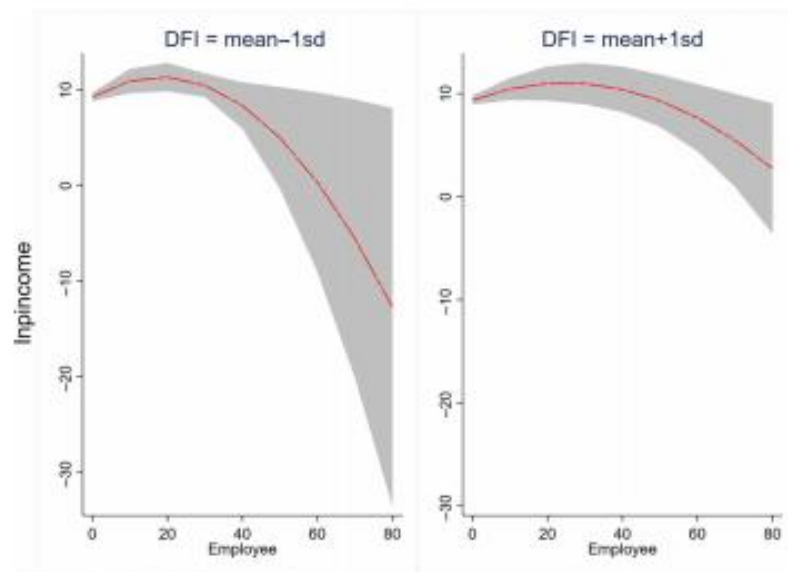


Figure 1.
Interaction effect of
Employ and *DFI* on
household income
(*DFI* = mean $\pm$ 1 sd)

Source(s): Authors' own work

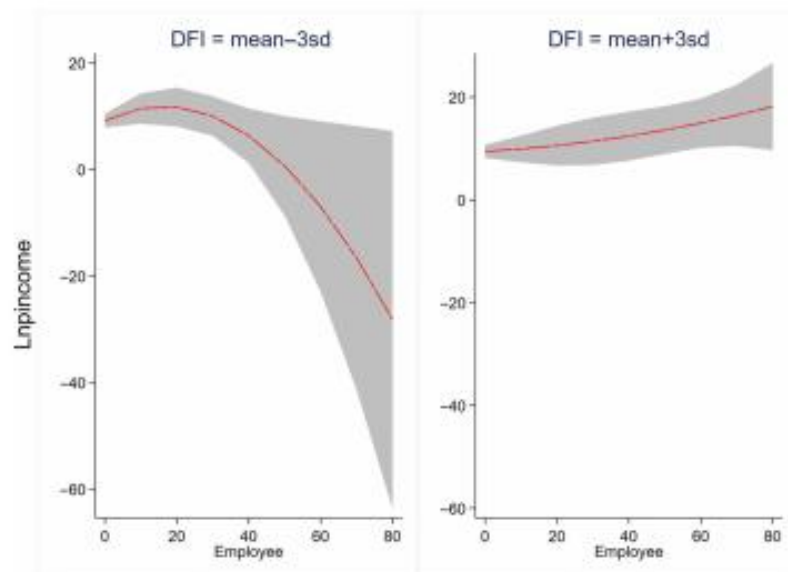


Figure 2.
Interaction effect of
Employ and *DFI* on
household income
(*DFI* = mean $\pm$ 3 sd)

Source(s): Authors' own work

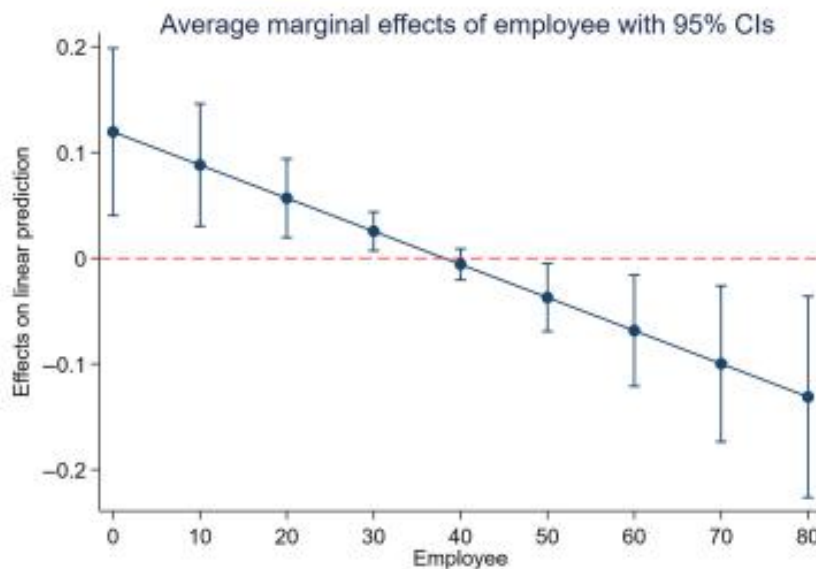
of digital finance, there is an inverted U-shaped curve between e-commerce participation and household income, supporting [Hypothesis 1](#). However, at higher levels of digital finance, the inverted U-shaped curve flattens. The Y-axis values also shift slightly upward at higher levels

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*². 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*²

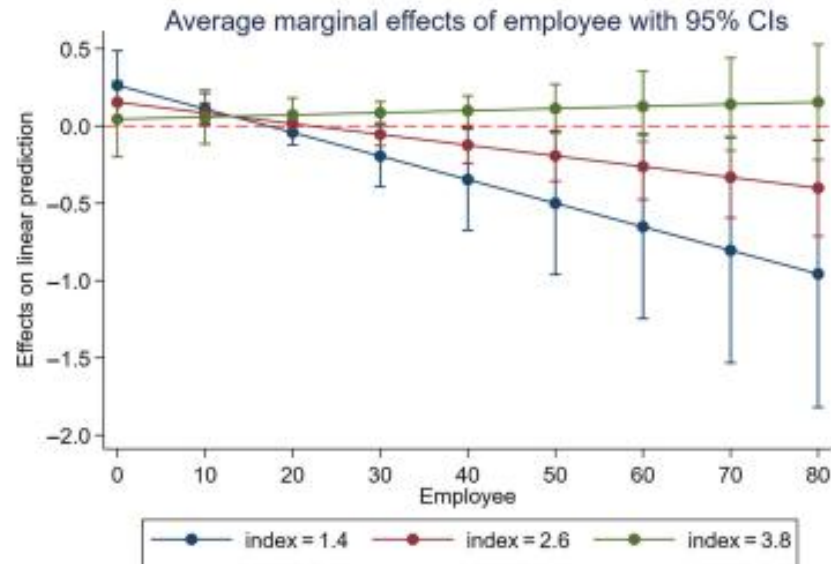


Figure 4.
Marginal effect with
 $Employ^2$ and
interaction item

Source(s): Authors' own work

Variables	(1) Two-step GMM	(2) Two-step GMM	(3) Two-step GMM	(4) Two-step GMM
<i>Employ</i>	0.1104*** (0.0257)	0.0894*** (0.0231)	0.1689 (0.1183)	0.2081* (0.1177)
$Employ^2$	-0.0014*** (0.0003)	-0.0011*** (0.0003)	-0.0086** (0.0031)	-0.0097** (0.0032)
<i>Employ</i> × <i>DFI</i>			0.0186 (0.0470)	0.0042 (0.0455)
$Employ^2$ × <i>DFI</i>			0.0017* (0.0010)	0.0021** (0.0010)
<i>DFI</i>			0.3867** (0.1537)	0.1552 (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 [0.000]	161.419 [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 [0.4985]	80.894 [0.6354]	181.934 [0.2188]	191.335 [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 β_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

CAER

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) <i>Lndebt</i>	(2) <i>Lnpincome</i>	(3) <i>Lninvest</i>	(4) <i>Lnpincome</i>	(5) <i>Risk</i>	(6) <i>Lnpincome</i>
<i>Employ</i>	1.2534 (0.8171)	0.2889 (0.2527)	2.1967*** (0.6907)	0.2852 (0.2510)	0.5469 (0.4786)	-0.0012 (0.7987)
<i>Employ</i> ²	-0.0506** (0.0219)	-0.0087 (0.0069)	-0.0704*** (0.0192)	-0.0090 (0.0068)	-0.0399** (0.0192)	-0.0255 (0.0352)
<i>Employ</i> × <i>DFI</i>	-0.3373 (0.3147)	-0.0657 (0.0929)	-0.6342*** (0.2298)	-0.0603 (0.0919)	-0.1251 (0.1530)	0.0395 (0.2419)
<i>Employ</i> ² × <i>DFI</i>	0.0152** (0.0072)	0.0023 (0.0022)	0.0208*** (0.0060)	0.0024 (0.0022)	0.0115** (0.0057)	0.0072 (0.0104)
<i>DFI</i>	3.3608** (1.6532)	0.5025 (0.4722)	-0.0846 (0.4310)	0.1190 (0.4272)	1.0701* (0.6244)	1.5555* (0.8558)
<i>Lndebt</i>		0.0077 (0.0041)				
<i>Lninvest</i>				0.0428*** (0.0097)		
<i>Risk</i>						0.1038*** (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> ² _{adj}	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

1. National Bureau of Statistics, China. Seventh National Census Bulletin (No.7). http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/qgrkpcgb/202106/t20210628_1818836.html
2. National Bureau of Statistics, China. Resident income and consumer spending in 2022. 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.

References

- Baum, C. and Lewbel, A. (2019), "Advice on using heteroskedasticity-based identification", *Stata Journal*, Vol. 19 No. 4, pp. 757-767.
- Benjamin, D., Brandt, L. and Giles, J. (2011), "Did higher inequality impede growth in rural China?", *The Economic Journal*, Vol. 121 No. 557, pp. 1281-1309.
- Berg, T. (2020), "On the rise of fintechs: credit scoring using digital footprints", *The Review of Financial Studies*, Vol. 33 No. 7, pp. 2845-2897.
- Bessant, J. (2008), "Dealing with discontinuous innovation: the European experience", *International Journal of Technology Management*, Vol. 42 Nos 1/2, pp. 36-50.
- Cheng, C., Chien, M. and Lee, C. (2021), "ICT diffusion, financial development, and economic growth: an international cross-country analysis", *Economic Modelling*, Vol. 94, pp. 662-671.
- Couture, V., Faber, B., Gu, Y. and Liu, L. (2021), "Connecting the countryside via e-commerce: evidence from China", *American Economic Review: Insights*, Vol. 3 No. 1, pp. 35-50.

- Das, A., Chowdhury, M. and Seaborn, S. (2018), "ICT diffusion, financial development and economic growth: new evidence from low and lower middle-income countries", *Journal of the Knowledge Economy*, Vol. 9 No. 3, pp. 928-947.
- Diagne, A., Zeller, M. and Sharma, M. (2000), "Empirical measurements of household's access to credit and credit constraints in developing countries", Food Consumption and Nutrition Division Discussion Paper 90, International Food Policy Research Institute, Washington, DC.
- Duan, J. and Cui, M. (2016), "Credit constraints, risk attitude and household asset choice", *Statistical Research*, Vol. 33 No. 6, pp. 62-71.
- Evans, O. (2018), "Digital agriculture: mobile phones, internet and agricultural development in Africa", *Actual Problems of Economics*, Vols 7-8, pp. 76-90.
- Feng, G. and Zhang, M. (2022), "The coupling coordination development of rural e-commerce and rural revitalization: a case study of 10 rural revitalization demonstration counties in Guizhou", *Procedia Computer Science*, Vol. 199, pp. 407-414.
- Ferrante, M. (2015), "E-commerce platforms: liability for trade mark infringement reflections on Chinese courts' practice and remedies against the sale of counterfeits on the internet", *Journal of Intellectual Property Law and Practice*, Vol. 10 No. 4, pp. 255-261.
- Fletschner, D. (2009), "Rural women's access to credit: market imperfections and intrahousehold dynamics", *World Development*, Vol. 37 No. 3, pp. 618-631.
- Fuster, A., Plosser, M., Schnabl, P. and Vickery, J. (2019), "The role of technology in mortgage lending", *The Review of Financial Studies*, Vol. 32 No. 5, pp. 1854-1899.
- Hong, C., Lu, X. and Pan, J. (2021), "FinTech adoption and household risk-taking", *BOFIT Discussion Papers*, Vol. 14, pp. 1-10A.
- Islam, N., Marinakis, Y., Majadillas, M.A., Fink, M. and Walsh, S.T. (2020), "Here there be dragons, a pre-roadmap construct for IoT service infrastructure", *Technological Forecasting and Social Change*, Vol. 155, 119073.
- Jensen, R. (2007), "The digital divide: information (technology), market performance, and welfare in the South Indian fisheries sector", *The Quarterly Journal of Economics*, Vol. 122 No. 3, pp. 879-924.
- Leong, C.M.L., Pan, S.L., Newell, S. and Cui, L. (2016), "The emergence of self-organizing e-commerce ecosystems in remote villages of China: a tale of digital", *MIS Quarterly*, Vol. 40 No. 2, pp. 475-484.
- Lewbel, A. (2012), "Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models", *Journal of Business and Economic Statistics*, Vol. 30 No. 1, pp. 67-80.
- Li, G. and Qin, J. (2022), "Income effect of rural e-commerce: empirical evidence from Taobao villages in China", *Journal of Rural Studies*, Vol. 96 No. 10, pp. 129-140.
- Li, X., Guo, H., Jin, S., Ma, W. and Zeng, Y. (2021), "Do farmers gain internet dividends from e-commerce adoption? Evidence from China", *Food Policy*, Vol. 101 No. 3, pp. 1-13.
- Li, J., Wu, Y. and Xiao, J.J. (2020), "The impact of digital finance on household consumption: evidence from China", *Economic Modelling*, Vol. 86, pp. 317-326.
- Lin, H., Li, R., Hou, S. and Li, W. (2021), "Influencing factors and empowering mechanism of participation in e-commerce: an empirical analysis on poor households from Inner Mongolia, China", *Alexandria Engineering Journal*, Vol. 60 No. 1, pp. 95-105.
- Lind, J.T. and Mehlum, H. (2010), "With or without U? The appropriate test for a U-shaped relationship", *Oxford Bulletin of Economics and Statistics*, Vol. 72 No. 1, pp. 109-118.
- Luo, X. and Niu, C. (2019), "E-commerce participation and household income growth in Taobao villages", World Bank Policy Research Working Paper Series No. 8811.
- Mishra, V. and Smyth, R. (2015), "Estimating returns to schooling in urban China using conventional and heteroskedasticity-based instruments", *Economic Modelling*, Vol. 47, pp. 166-173.

- Peng, C., Ma, B. and Zhang, C. (2021), "Poverty alleviation through e-commerce: village involvement and demonstration policies in rural China", *Journal of Integrative Agriculture*, Vol. 20 No. 4, pp. 998-1011.
- Pradhan, R.P., Arvin, M.B., Nair, M.S., Hall, J.H. and Bennett, S.E. (2021), "Sustainable economic development in India: the dynamics between financial inclusion, ICT development, and economic growth", *Technological Forecasting and Social Change*, Vol. 169 No. 3, pp. 1-19.
- Rothstein, B. and Uslaner, E.M. (2005), "All for all: equality, corruption, and social trust", *World Politics*, Vol. 58 No. 1, pp. 41-72.
- Shamim, F. (2007), "The ICT environment, financial sector and economic growth: a cross-country analysis", *Journal of Economic Studies*, Vol. 34 No. 4, pp. 352-370.
- Tang, W. and Zhu, J. (2020), "Informality and rural industry: rethinking the impacts of e-commerce on rural development in China", *Journal of Rural Studies*, Vol. 75 No. 1, pp. 20-29.
- Teece, D.J. (2009), "Business models, business strategy and innovation", *Long Range Planning*, Vol. 43 No. 2, pp. 172-194.
- Townsend, D.M., Hunt, R.A., McMullen, J.S. and Sarasvathy, S.D. (2018), "Uncertainty, knowledge problems, and entrepreneurial action", *The Academy of Management Annals*, Vol. 12 No. 2, pp. 659-687.
- Vakulenko, Y., Shams, P., Hellstrom, D. and Hjort, K. (2019), "Service innovation in e-commerce last mile delivery: mapping the e-customer journey", *Journal of Business Research*, Vol. 101 No. 8, pp. 461-468.
- Vitores, A. and Gil-Juárez, A. (2015), "The trouble with 'women in computing': a critical examination of the deployment of research on the gender gap in computer science", *Journal of Gender Studies*, Vol. 25 No. 6, pp. 666-680.
- Wang, C., Tong, Q., Xia, C., Shi, M. and Cai, Y. (2022), "Does participation in e-commerce affect fruit farmers' awareness of green production: evidence from China", *Journal of Environmental Planning and Management*, doi: 10.1080/09640568.2022.2133686.
- Wei, X. and Ruan, J. (2022), "Influences of government policies and farmers' cognition on farmers' participation willingness and behaviors in E-commerce Interest linkage mechanisms during farmer-enterprise games", *Agriculture*, Vol. 12, 1625.
- Wellalage, N.H. and Fernandez, V. (2019), "Innovation and SME finance: evidence from developing countries", *International Review of Financial Analysis*, Vol. 66, 101370.
- Xu, Y., Peng, Z., Sun, Z., Zhan, H. and Li, S. (2022), "Does digital finance lessen credit rationing? — evidence from Chinese farmers", *Research in International Business and Finance*, Vol. 62, pp. 1-15.
- Zhao, X., Cui, Z. and Zhao, F. (2022), "Does e-commerce participation affect green agrotechnology adoption among reservoir resettlers? The case of China's three gorges reservoir area", *Frontiers in Environmental Science*, Vol. 10, 1036464.

(The Appendix follows overleaf)

Variables	E-commerce participation		
	(1) Breadth of coverage	(2) Depth of use	(3) Degree of digitization
<i>Employ</i>	0.3217 (0.2575)	0.3366* (0.1925)	0.6136** (0.2367)
<i>Employ</i> ²	-0.0121 (0.0069)	-0.0102* (0.0054)	-0.0177** (0.0062)
<i>Employ</i> × <i>Cover</i>	-0.0645 (0.1031)		
<i>Employ</i> ² × <i>Cover</i>	0.0034 (0.0023)		
<i>Cover</i>	1.3245* (0.7585)		
<i>Employ</i> × <i>Usage</i>		-0.0718 (0.0733)	
<i>Employ</i> ² × <i>Usage</i>		0.0027 (0.0018)	
<i>Usage</i>		-0.1764 (0.2529)	
<i>Employ</i> × <i>Digit</i>			-0.1384* (0.0713)
<i>Employ</i> ² × <i>Digit</i>			0.0042** (0.0016)
<i>Digit</i>			0.0096 (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> ² _{adj}	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) Non-poor	(2) Poor	(3) Male	(4) Female
<i>Employ</i>	0.4159* (0.2483)	-5.3756** (2.6678)	0.3117 (0.2339)	0.9132* (0.4939)
<i>Employ</i> ²	-0.0132** (0.0067)	2.6799*** (0.9018)	-0.0345* (0.0193)	0.0468 (0.0309)
<i>Employ</i> × <i>DFT</i>	-0.0968 (0.0925)	1.8992 (1.1467)	-0.0563 (0.0796)	-0.1416 (0.1896)
<i>Employ</i> ² × <i>DFT</i>	0.0036 (0.0021)	-1.0221** (0.3956)	0.0099 (0.0055)	-0.0316 (0.0164)
<i>DFT</i>	-0.0369 (0.4401)	2.6128 (1.8355)	0.0011 (0.4572)	0.1968 (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> ² _{adj}	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) East	(2) Central	(3) West	(4) Northeast
<i>Employ</i>	0.6510** (0.2965)	-4.8563** (1.9552)	0.2388 (2.2676)	6.5580 (5.2290)
<i>Employ</i> ²	-0.0209*** (0.0072)	0.6367** (0.2486)	1.0408 (1.0835)	-7.6708 (6.1425)
<i>Employ</i> × <i>DFI</i>	-0.1513 (0.1150)	1.7433* (0.6896)	0.1423 (1.0581)	-2.3329 (2.1386)
<i>Employ</i> ² × <i>DFI</i>	0.0057** (0.0024)	-0.2240** (0.0864)	-0.5251 (0.5062)	3.0635 (2.4316)
<i>DFI</i>	0.4595 (0.9587)	-0.7255 (2.1701)	2.1710 (1.8536)	4.4048 (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> ² _{adj}	0.0757	0.0587	0.0457	0.0250

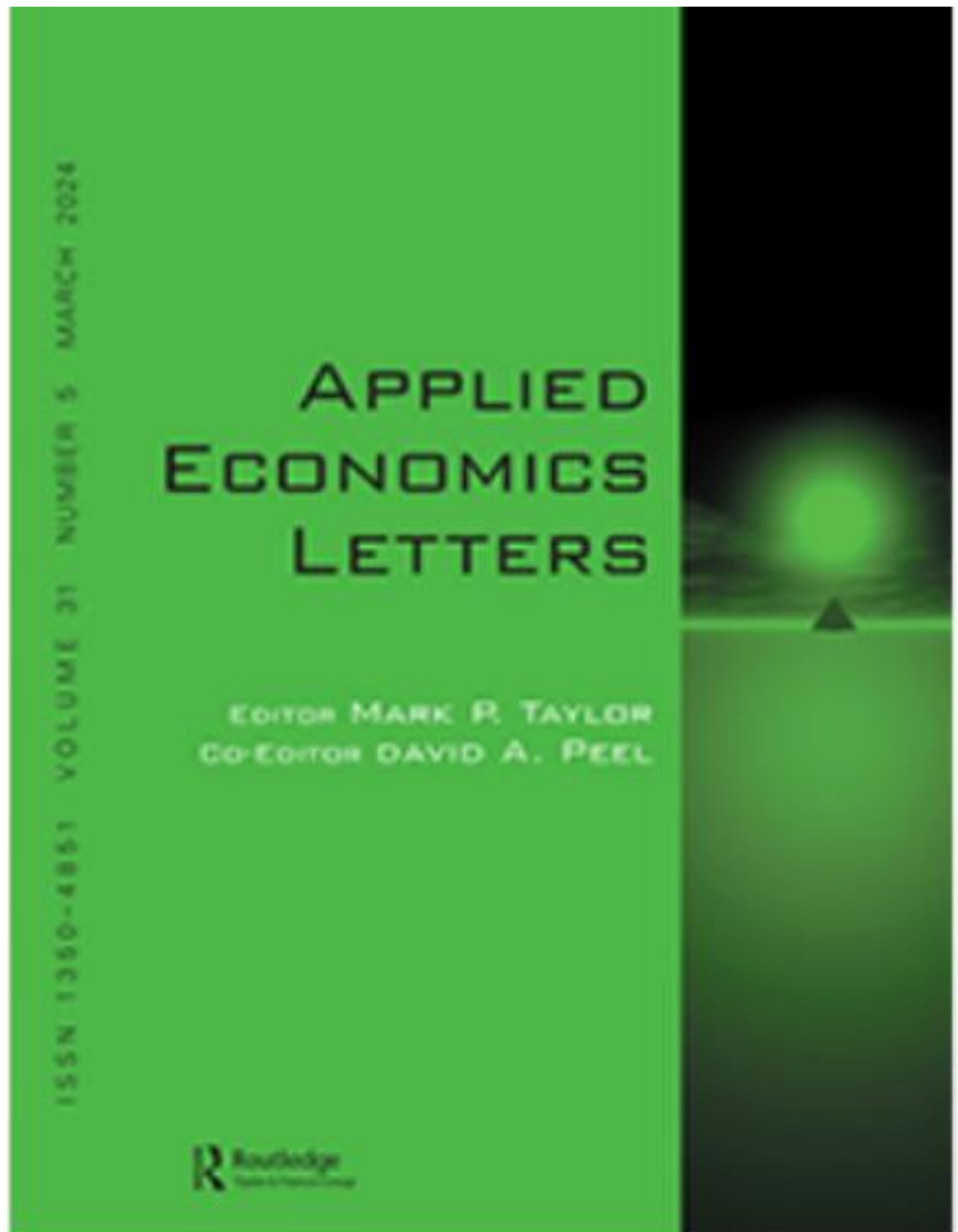
Table A4. Note(s): Control variables consistent with Table 2; Standard errors in parentheses clustered to city level; Heterogeneity analysis **p* < 0.1, ***p* < 0.05, ****p* < 0.01
II: macro perspective Source(s): Authors' own work

Corresponding author

Yi Cai can be contacted at: caiyl@scau.edu.cn

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgroupublishing.com/licensing/reprints.htm
 Or contact us for further details: permissions@emeraldinsight.com

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



Home Applied Economics Letters Journal Home Volume 31, Issue 5

Applied Economics Letters

Submit Abstract Browse Submit

View all articles and books

Volume 31, 2024

Year 31, Issue 5, Pages 451-510

Download all articles (27) Download all PDFs (27) Download all figures (0)

Display order: (Default) | Sort by: (Default) | Filter by: (Default)

Research Articles

The temporal-spatial evolution of China's active high-tech complexity Yanbin Chen, Xinyi Wang Pages: 451-460 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
Multi-factor style rotation – an empirical study in the US stock market Yongxin Li, Jiaxin Chen Pages: 461-480 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
Urbanization and industrial energy intensity in Eastern China Yiqun Wang Pages: 481-490 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	87 Pages 0 Downloaded 0 Abstracts
Financial development and FDI inflows: amplifying effect of bilateral political relations Jianfeng Wang, Jiaxin Chen Pages: 491-500 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
Industrial location and selection strategy of capital on the labour force in logistics enterprises: evidence from China and the United States Wenjie Wang, Jiaxin Chen, Jiaxin Chen Pages: 501-510 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
Asymmetric opportunities and event impacts on liquidity risk Yanbin Chen, Xinyi Wang, Jiaxin Chen Pages: 511-520 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
Measuring the persistence degree of stocks in the US financial markets: new evidence for COVID-19 pandemic period Yiqun Wang, Jiaxin Chen, Jiaxin Chen Pages: 521-530 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	87 Pages 0 Downloaded 0 Abstracts
The effect of the industrial networks within business groups on the quality of accounting information: evidence from China Yiqun Wang, Jiaxin Chen, Jiaxin Chen Pages: 531-540 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	87 Pages 0 Downloaded 0 Abstracts
Impact of Syrian refugees on house prices in Istanbul Yanbin Chen, Xinyi Wang, Jiaxin Chen Pages: 541-550 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
The impact of pandemic, environment, and facility Yanbin Chen, Xinyi Wang, Jiaxin Chen Pages: 551-560 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts
The impact of economic activities on rural household savings Yanbin Chen, Xinyi Wang, Jiaxin Chen Pages: 561-570 Published online: 27 July 2024 Abstract Full Text (Subscription) PDF Full Text (Open Access)	100 Pages 0 Downloaded 0 Abstracts

ARTICLE



The impact of e-commerce activities on rural household leverage

Lihao Yao ^{ab}, Famin Yi^{a,b} and Yi Cui^{a,b,c}

^aCollege of Economics and Management, South China Agricultural University, Guangzhou, China; ^bDigital Countryside Research Institute, South China Agricultural University, Guangzhou, China; ^cResearch Center for Green Development of Agriculture, South China Agricultural University, Guangzhou, China

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 leverage_{ist} is the household leverage of householders i in provinces in year t , which is equal to household debt divided by household assets.¹ The main explanatory variable 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. γ_i represents individual fixed effects and ε_{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 β_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

¹As 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/ HH asset	HH debt/ HH asset	HH debt/ HH asset	HH debt/ HH income	HH bank debt/ HH asset	HH nonbank debt/ HH asset	HH time deposits/ HH asset	HH demand deposits/ HH asset
ECA_dummy	0.033* (0.019)	0.542* (0.291)		1.257* (0.758)	0.377*** (0.137)	0.100 (0.233)	0.348 (0.265)	0.145 (0.176)
ECA_freq			0.146* (0.086)					
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
First-stage: vill_avgtime		0.003** (0.001)	0.014*** (0.005)	0.003* (0.002)	0.003** (0.001)	0.003** (0.001)	0.001 (0.002)	0.002 (0.003)
lnuser		0.317*** (0.078)	1.045*** (0.305)	0.322*** (0.083)	0.317*** (0.078)	0.317*** (0.078)	0.390*** (0.129)	0.374*** (0.132)
Control variables		Y	Y	Y	Y	Y	Y	Y
Individual FE		Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap rk LM statistic		12.926*** (0.0016)	12.520*** (0.0019)	11.477*** (0.0032)	12.926*** (0.0016)	12.926*** (0.0016)	7.769** (0.0206)	6.939** (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 (0.3715)	1.226 (0.2682)	0.236 (0.6273)	0.260 (0.6103)	0.398 (0.5282)	2.701 (0.1003)	0.683 (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 (0.726)	0.394 (0.891)	0.426* (0.221)	0.560 (1.139)	0.439 (0.275)	0.478 (1.642)	1.154** (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.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Social Science Foundation of China [19BGL256].

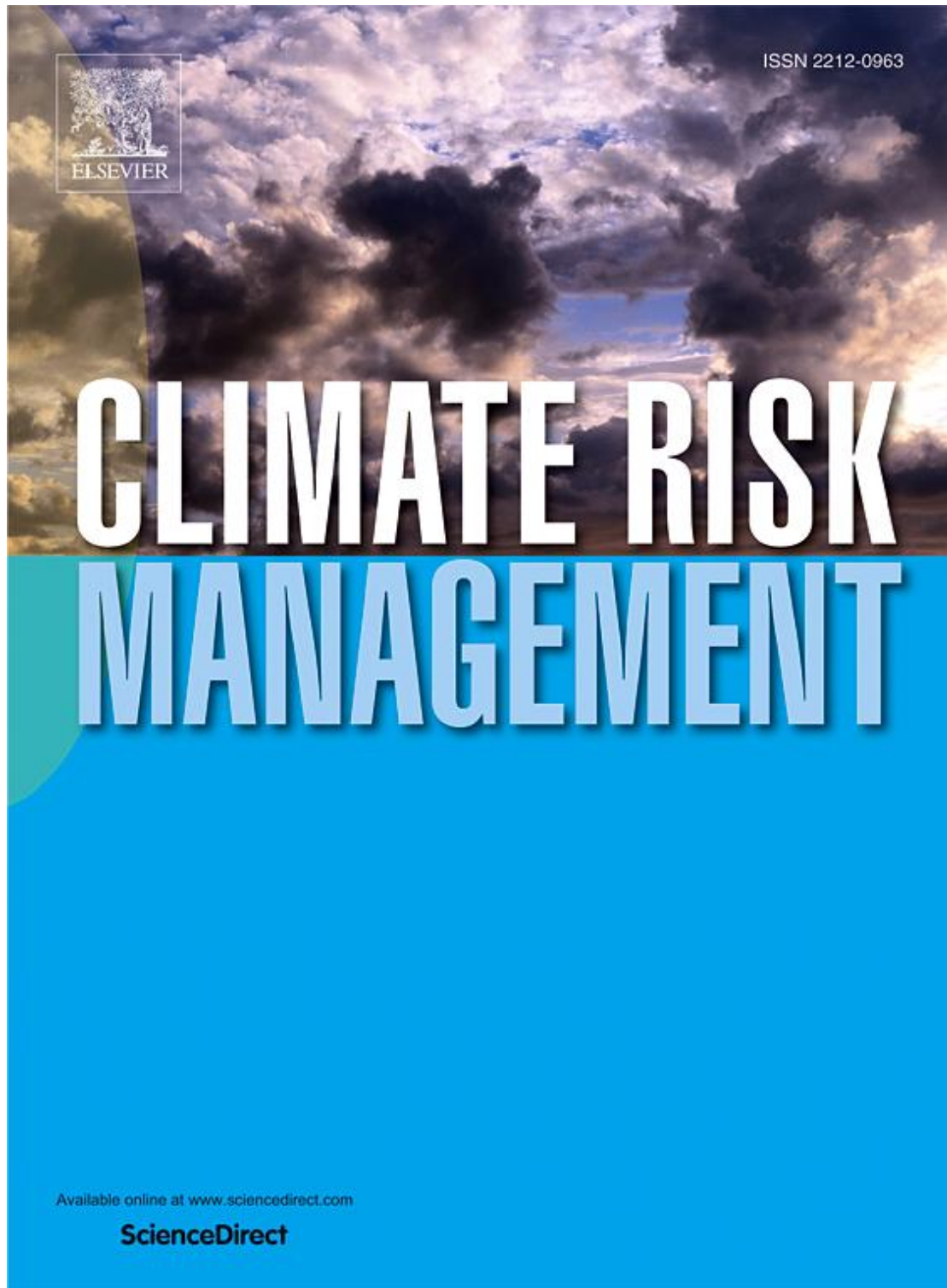
ORCID

Lihao Yao  <http://orcid.org/0000-0001-8554-3263>

References

- Bahta, Y. T., D. B. Strydom, and E. Donkor. 2017. "Microcredit and Gender Empowerment: Policy Implications for Sustainable Agricultural Development in Eritrea." *Development in Practice* 27 (1): 90–102. doi:10.1080/09614524.2017.1259393.
- Croson, R., and U. Gneezy. 2009. "Gender Differences in Preferences." *Journal of Economic Literature* 47: 448–474. doi:10.1257/jel.47.2.448.
- Dong, L., L. Ren, and D. Zhang. 2019. "Financing Small and Medium-Size Enterprises via Retail Platforms." *Social Science Electronic Publishing*. doi:10.2139/ssrn.3257899.
- Dunt, E. S., and I. R. Harper. 2002. "E-Commerce and the Australian Economy." *The Economic Record* 78 (242): 327–342. doi:10.1111/1475-4932.00061.
- Goldfarb, A., and C. Tucker. 2019. "Digital Economics." *Journal of Economic Literature* 57 (1): 3–43. doi:10.1257/jel.20171452.
- Leroux, N., M. S. Wortman, and E. D. Mathias. 2001. "Dominant Factors Impacting the Development of Business-to-Business(B2B) E-Commerce in Agriculture." *International Food and Agribusiness Management Review* 4 (2): 205–218. doi:10.1016/S1096-7508(01)00075-1.
- Li, C., L. Lin, and C. E. C. Gan. 2016. "China Credit Constraints and Rural Households' Consumption Expenditure." *Finance Research Letters* 19: 158–164. doi:10.1016/j.frl.2016.07.007.
- Li, Y., and X. Zhang. 2020. *National Balance Sheet of China 2020 (Chinese)*. Beijing: China Social Sciences Press. doi:10.1007/978-981-10-4385-7.
- Peng, Y. L., Y. Ren, and H. Li. 2021. "Do Credit Constraints Affect Households' Economic Vulnerability? Empirical Evidence from Rural China." *Journal of Integrative Agriculture* 20 (9): 2552–2568. doi:10.1016/S2095-3119(20)63557-2.
- Shamim, F. 2007. "The ICT Environment, Financial Sector and Economic Growth: A Cross-Country Analysis." *Journal of Economic Studies* 34 (4): 352–370. doi:10.1108/01443580710817452.
- Stiglitz, J. E., and A. Weiss. 1981. "Credit Rationing in Markets with Imperfect Information." *American Economic Review* 71: 393–410. doi:10.2307/1802787.
- Wahidi, I. 2017. "Microcredit in Lebanon: First Data on Its Beneficiaries." *International Business Research* 10 (4): 32–41. doi:10.5539/ibr.v10n4p32.
- Zhang, Y., H. Long, L. Ma, S. Tu, Y. Li, and D. Ge. 2018. "Analysis of Rural Economic Restructuring Driven by E-Commerce Based on the Space of Flows: The Case of Xiaying Village in Central China." *Journal of Rural Studies* 12: 1–13. doi:10.1016/j.jrurstud.2018.12.001.
- Zhao, J. M., and J. B. Peter. 2014. "Effects of Credit Constraints on Rural Household Technical Efficiency: Evidence from a City in Northern China." *China Agricultural Economic Review* 6: 654–668. doi:10.1108/CAER-10-2012-0115.
- Zhou, X., Y. Cui, and S. Zhang. 2020. "Internet Use and Rural Residents' Income Growth." *China Agricultural Economic Review* 12 (2): 315–327. doi:10.1108/CAER-06-2019-0094.

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





Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

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

Muhammad Faisal^a, Azhar Abbas^b, Chunping Xia^{a,*}, Muhammad Haseeb Raza^g, Shoaib Akhtar^c, Muhammad Arslan Ajmal^d, Zulqarnain Mushtaq^e, Yi Cai^{f,*}^a College of Economics and Management, Huazhong Agricultural University, Wuhan 430070, Hubei Province, PR China^b Institute of Agricultural and Resource Economics, University of Agriculture Faisalabad, 38040, Pakistan^c Center of Excellence for Olive Research & Training (CEFORT), Barani Agriculture Research Institute (BARI), Chakwal, Pakistan^d Department of Economics, Government College University, Faisalabad, 38000, Pakistan^e School of Economics and Finance, Xi'an Jiaotong University, Xi'an, Shaanxi, PR China^f College of Economics and Management, Digital Countryside Research Institute, South China Agricultural University, Guangzhou 510640, PR China^g Institute of Business Management Sciences, University of Agriculture Faisalabad, 38000, Pakistan

ARTICLE INFO

Keywords:

Adaptation measures

Climate change

Livestock losses

Poverty

Propensity score matching (PSM)

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.

* Corresponding authors.

E-mail addresses: faisalgurmani@gmail.com (M. Faisal), Azhar.Abbas@uaf.edu.pk (A. Abbas), xcp@mail.hzau.edu.cn (C. Xia), haseebzvi00@yahoo.com (M. Haseeb Raza), shoaibakhtar1799@gmail.com (S. Akhtar), arslan.gogo7@gmail.com (M. Arslan Ajmal), Zulqarnain@stu.xjtu.edu.cn (Z. Mushtaq), cai.yi@scau.edu.cn (Y. Cai).

<https://doi.org/10.1016/j.crm.2021.100358>

Received 7 December 2020; Received in revised form 16 August 2021; Accepted 31 August 2021

Available online 3 September 2021

2212-0963/© 2021 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license

<http://creativecommons.org/licenses/by-nc-nd/4.0/>

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

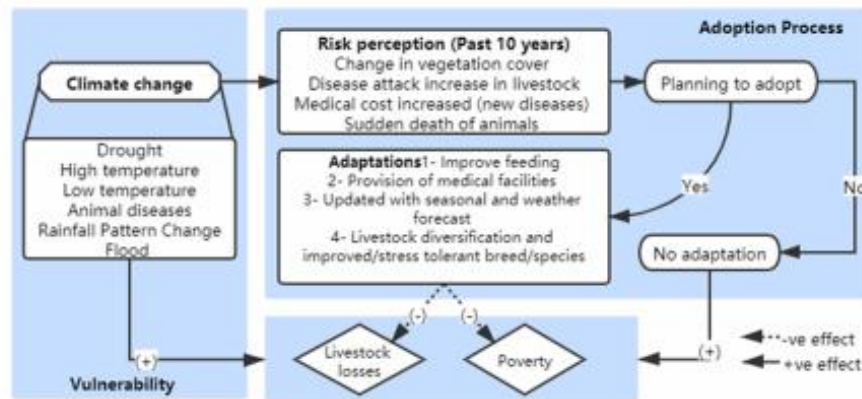


Fig. 1. Conceptual framework of the study.

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, β_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 ϵ_i . α , δ are the regression coefficient, X_{ij} represents the vector of independent variables and λ and μ_i are respectively the logistic regression coefficient and its error term. It might be possible that the decision to adopt β_i is assumed to be independent, which may be influenced by some unknown factor(s) that form the error term ϵ_i . Moreover ϵ_i may be correlated with μ_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 β_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, I 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.

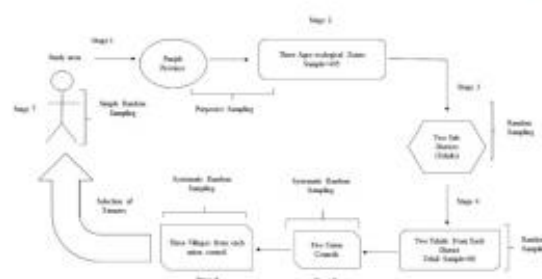


Fig. 2. Data collection framework and Sampling technique.

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
Independent variable			
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
Dependent variables (adaptation: 1 if adopted, 0 otherwise)			
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
Outcome variables			
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
Other climate related risk perceptions of livestock herders (not used in empirical analysis)			
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 adopted 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		1 ^a	2 ^b	3 ^c	4 ^d		
	Coefficient (Std. Err.)		Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)		
Age	-0.015**	(0.008)	-0.017	(0.016)	-0.047*	(0.027)	-0.024	(0.026)
Education	0.055***	(0.013)	0.038	(0.034)	0.200***	(0.045)	0.184***	(0.043)
Experience	0.018**	(0.008)	0.036**	(0.017)	0.042	(0.027)	0.030	(0.027)
Household type	0.355***	(0.108)	0.696***	(0.249)	0.828**	(0.340)	0.803**	(0.327)
Household size	0.009*	(0.005)	0.056**	(0.026)	0.017	(0.018)	0.017	(0.019)
Off farm income	-0.227**	(0.109)	-0.236	(0.286)	-0.739**	(0.361)	-0.476	(0.362)
Distance to market	-0.005	(0.007)	-0.002	(0.019)	-0.019	(0.022)	-0.034	(0.022)
Operational land holding	0.003	(0.004)	0.019	(0.013)	-0.003	(0.014)	0.003	(0.014)
Area under heard	-0.005	(0.008)	0.025	(0.033)	-0.055*	(0.031)	0.045	(0.035)
Govt. veterinary center	0.238**	(0.106)	0.313	(0.252)	0.489	(0.332)	1.017***	(0.329)
Livestock helpline	0.502***	(0.176)	0.543	(0.525)	1.821**	(0.574)	0.325	(0.573)
Private doctor availability	0.399***	(0.127)	0.450	(0.285)	0.484	(0.398)	0.893**	(0.390)
Satisfactory veterinary facilities	0.373***	(0.119)	0.696**	(0.282)	0.507	(0.365)	0.563	(0.362)
Extension services	0.650***	(0.121)	0.789***	(0.257)	1.637***	(0.384)	1.362***	(0.358)
Credit availability	0.010	(0.111)	-0.625**	(0.288)	0.504	(0.358)	0.595*	(0.346)
Dera Ghazi Khan	0.157	(0.146)	0.100	(0.362)	2.084***	(0.507)	-0.322	(0.464)
Rahim Yar Khan	-0.056	(0.137)	-0.372	(0.368)	1.057**	(0.464)	-1.029**	(0.457)
Faisalabad	(omitted)		(omitted)		(omitted)		(omitted)	
Constant	-1.303***	(0.342)	-2.074***	(0.791)	-4.842***	(1.086)	-4.516***	(1.085)
Log pseudo likelihood	-492.337		-224.658		-150.785		-156.295	
Wald chi2	253.470		103.510		139.670		172.530	
Pseudo R ²	0.205		0.187		0.317		0.356	

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

^a Improve feeding (grazing management, diet supplementation, practicing concentrate and bran feeding).

^b Provision of medical facilities (disease control precaution, involve in some kind livestock training).

^c Updated with seasonal and weather forecast information.

^d 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 4th 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 ^e	1 ^a				2 ^b				3 ^c				4 ^d				
	Balance test		Reducte Bias %	T-test	Mean		Reducte Bias %	T-test	Mean		Reducte Bias %	T-test	Mean		Reducte Bias %	T-test	
	Unmatched	Matched			Treated	Control			Treated	Control			Treated	Control			Treated
1	U	43.94	45.01	-153.20	-0.96	41.66	45.23	87.00	-2.75***	41.82	45.43	74.90	-2.98***	40.84	45.11	54.70	-2.91***
	M	43.89	41.16		2.74***	41.79	42.25		-0.32	42.13	41.23		0.61	40.23	38.30		1.33
2	U	6.43	4.27	-1.90	4.94***	8.11	4.71	80.70	6.81***	8.75	4.20	78.80	10.36***	8.50	4.90	53.10	6.32***
	M	6.47	8.68		-4.82***	8.02	8.68		-1.07	8.49	9.45		-1.88	8.56	10.25		-2.87
3	U	22.65	21.24	-89.40	1.33	21.13	22.33	-20.70	-0.98	21.00	22.47	67.50	-1.27	20.66	22.33	-101.80	-1.19
	M	22.62	19.96		2.96***	21.18	22.63		-1.05	21.16	20.69		0.36	20.19	16.83		2.41**
4	U	0.72	0.51	79.30	4.45***	0.77	0.59	46.60	3.24***	0.79	0.56	87.50	4.41***	0.78	0.60	65.30	2.82***
	M	0.72	0.76		-1.07	0.76	0.67		1.46	0.78	0.81		-0.51	0.78	0.84		-0.90
5	U	11.26	8.18	23.90	4.16***	12.99	9.01	96.80	4.03***	12.17	9.05	98.20	3.85***	12.88	9.35	65.50	3.59***
	M	10.95	8.61		3.57***	12.93	13.05		-0.08	11.77	11.71		0.04	11.94	13.16		-0.70
6	U	0.69	0.54	37.90	3.06***	0.67	0.61	-59.90	1.18	0.74	0.57	43.00	3.16***	0.72	0.60	20.70	1.84*
	M	0.69	0.78		-2.22**	0.68	0.78		-1.66	0.73	0.83		-1.67*	0.73	0.83		-1.28
7	U	16.07	14.79	68.40	1.62	14.93	15.70	50.20	-0.84	16.42	15.16	-3.30	1.47	16.91	15.24	12.10	1.61
	M	16.07	16.47		-0.51	15.02	14.63		0.33	16.90	18.20		-1.29	17.20	15.73		1.27
8	U	10.68	6.09	78.20	3.77***	13.45	7.27	94.60	4.36***	12.88	7.05	68.30	4.40***	13.11	7.83	54.90	3.26***
	M	10.38	9.38		0.83	13.28	12.95		0.16	11.58	9.73		1.29	11.59	13.97		-1.04
9	U	8.09	4.78	82.20	4.49***	8.77	6.04	80.30	3.13***	9.39	5.59	86.70	4.71***	12.37	5.53	84.50	7.27***
	M	7.85	8.44		-0.84	8.88	9.42		-0.40	7.93	7.43		0.53	10.64	9.58		0.69
10	U	0.63	0.49	15.10	2.70***	0.74	0.52	95.10	3.86***	0.76	0.49	100.00	5.05***	0.76	0.53	86.80	3.64***
	M	0.62	0.51		2.46**	0.73	0.74		-0.17	0.74	0.74		0.00	0.75	0.72		0.40
11	U	0.24	0.09	94.00	3.84***	0.29	0.14	100.00	3.54***	0.28	0.13	93.80	3.71***	0.41	0.13	100.00	5.84***
	M	0.23	0.24		-0.22	0.30	0.30		0.00	0.24	0.23		0.16	0.38	0.38		0.00
12	U	0.73	0.48	79.30	5.37***	0.78	0.58	41.30	3.60***	0.84	0.54	72.20	6.04***	0.90	0.57	95.20	5.24***
	M	0.73	0.79		-1.31	0.78	0.90		-2.24**	0.83	0.91		-1.86*	0.89	0.88		0.27
13	U	0.68	0.44	83.70	5.01***	0.79	0.51	88.30	4.90***	0.81	0.48	62.00	6.27***	0.88	0.52	91.50	5.79***
	M	0.68	0.72		-0.92	0.78	0.82		-0.55	0.80	0.68		2.05**	0.88	0.84		0.51
14	U	0.72	0.44	84.40	5.93***	0.86	0.52	90.60	6.25***	0.84	0.50	55.60	6.70***	0.93	0.53	100.00	6.30***
	M	0.72	0.76		-1.07	0.86	0.89		-0.67	0.83	0.68		2.59**	0.92	0.92		0.00
15	U	0.44	0.39	53.80	1.14	0.60	0.36	77.20	4.14***	0.59	0.35	84.50	4.63***	0.56	0.39	72.00	2.56**
	M	0.44	0.41		0.57	0.59	0.65		-0.75	0.55	0.51		0.55	0.53	0.58		-0.53
16	U	0.33	0.34	-679.00	-0.28	0.44	0.30	47.00	2.59***	0.30	0.35	35.50	-0.85	0.26	0.35	81.10	-1.32
	M	0.32	0.22		2.54**	0.43	0.35		1.05	0.27	0.24		0.47	0.22	0.23		-0.21
17	U	0.32	0.35	-345.10	-0.50	0.32	0.34	53.10	-0.41	0.25	0.37	-14.20	-2.26**	0.31	0.34	-218.30	-0.47
	M	0.33	0.22		2.52**	0.32	0.33		-0.16	0.28	0.14		2.39**	0.33	0.23		1.18
18	U	0.35	0.31	-466.50	0.78	0.24	0.36	45.90	-2.16**	0.45	0.29	-0.50	3.14***	0.43	0.31	30.20	1.79*
	M	0.35	0.56		-4.60***	0.25	0.31		-0.98	0.46	0.62		-2.37**	0.45	0.53		-0.88

^a Improved feeding (grazing management, diet supplementation, pre-feeding concentrate and bran feeding), ^b Provision of medical facilities (disease control, prevention, involve in some kind livestock training), ^c Updated with seasonal and weather forecast information, ^d Livestock diversification and improved/stress-tolerant breed/species, ^e (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 = Govt. veterinary center, 11 = Livestock helpline, 12 = Private doctor availability, 13 = Satisfactory veterinary facilities, 14 = Extension services, 15 = Credit availability, 16 = Dera Ghazi 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.

Acknowledgments

This research was supported by The Youth Project of Guangdong Provincial Department of Education (2020WQNCX006) and the special funds for the development of high level universities (4700-220140).

References

- Smith, J.A., Todd, P.E., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *J. Econom.* 125 (1-2), 305-353. <https://doi.org/10.1016/j.jeconom.2004.04.011>.

- Abate, T., Shiferaw, B., Menkir, A., Wegary, D., Kebede, Y., Tesfaye, K., Kassie, M., Bogale, G., Tadesse, B., Keno, T., 2015. Factors that transformed maize productivity in Ethiopia. *Food Secur.* 7 (5), 965–981. <https://doi.org/10.1007/s12571-015-0488-z>.
- Abid, M., Schneider, U.A., Scheffran, J., 2016. Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan. *J. Rural Stud.* 47, 254–266. <https://doi.org/10.1016/j.jrurstud.2016.08.005>.
- Akhtar, S., Li, G., Cheng, Nazir, A., Razaq, A., Ullah, R., Faisal, M., Naseer, M.A.U.R., Raza, M.H., 2019. Maize production under risk: The simultaneous adoption of off-farm income diversification and agricultural credit to manage risk. *J. Integr. Agric.* 18, 460–470. [https://doi.org/10.1016/S2095-3119\(18\)61968-9](https://doi.org/10.1016/S2095-3119(18)61968-9).
- Akhtar, S., Abbas, A., Iqbal, M., Rizwan, M., Agriculture, A.S., 2021, undefined, 2021. What Determines the Uptake of Multiple Tools to Mitigate Agricultural Risks among Hybrid Maize Growers in Pakistan? Findings from Field-Level Data. *mdpi.com*. <https://doi.org/10.3390/agriculture11070578>.
- Akhtar, S., Li, G.-C., Ullah, R., Nazir, A., Iqbal, M.A., Raza, M.H., Iqbal, N., Faisal, M., 2018. Factors influencing hybrid maize farmers' risk attitudes and their perceptions in Punjab Province, Pakistan. *J. Integr. Agric.* 17 (6), 1454–1462. [https://doi.org/10.1016/S2095-3119\(17\)61796-9](https://doi.org/10.1016/S2095-3119(17)61796-9).
- Akudugu, M.A., Guo, E., Dadzie, S.K., 2012. Adoption of modern agricultural production technologies by farm households in Ghana: what factors influence their decisions? *J. Biol. Agric. Healthc.* 2, 1–13.
- Ali, A., Abdulai, A., 2010. The adoption of genetically modified cotton and poverty reduction in Pakistan. *J. Agric. Econ.* 61, 175–192. <https://doi.org/10.1111/j.1477-9552.2009.00227.x>.
- Ali, A., Bahadur Rahut, D., Behera, B., 2016. Factors influencing farmers' adoption of energy-based water pumps and impacts on crop productivity and household income in Pakistan. *Renew. Sustain. Energy Rev.* 54, 48–57. <https://doi.org/10.1016/j.rser.2015.09.073>.
- Ali, A., Erenstein, O., 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Clim. Risk Manage.* 16, 183–194. <https://doi.org/10.1016/j.crm.2016.12.001>.
- Ali, A., Rahut, D.B., Mottaleb, K.A., 2018. Improved water-management practices and their impact on food security and poverty: empirical evidence from rural Pakistan. *Water Policy* 20, 692–711. <https://doi.org/10.2166/wp.2018.044>.
- Ali, A., Rahut, D.B., 2018. Forest-based livelihoods, income, and poverty: empirical evidence from the Himalayan region of rural Pakistan. *J. Rural Stud.* 57, 44–54.
- Bangalore, M., Smith, A., Veldkamp, T., 2017. Exposure to floods, climate change, and poverty in vietnam. *Nat. Hazards Earth Syst. Sci. Discuss.* 3, 1–28. <https://doi.org/10.5194/nhess-2017-100>.
- Banik, S., Panikaj, P.K., Naskar, S., 2015. Climate change: impacts on livestock diversity in tropical countries. *Livest. Prod. Clim. Chang.* 162–182. <https://doi.org/10.1079/9781780644325.0162>.
- Bastakoti, R.C., Gupta, J., Babel, M.S., van Dijk, M.P., 2014. Climate risks and adaptation strategies in the Lower Mekong River basin. *Reg. Environ. Chang.* 14 (1), 207–219. <https://doi.org/10.1007/s10113-013-0485-8>.
- Benfica, R., Canguana, B., Thurlow, J., 2018. Linking agricultural investments to growth and poverty: An economywide approach applied to Mozambique. *Agric. Syst. Berhannu, K., Poulton, C., 2014. The Political Economy of Agricultural Extension Policy in Ethiopia: Economic Growth and Political Control. Dev. Policy Rev.* 32, s199–s216. <https://doi.org/10.1111/dpr.12082>.
- Bernabucci, U., 2019. Climate change: impact on livestock and how can we adapt. *Anim. Front.* 9, 1–5. <https://doi.org/10.1093/af/vfy039>.
- Bett, B., Kunga, P., Gachohi, J., Sindato, C., Mborha, D., Robinson, T., Lindahl, J., Grace, D., 2017. Effects of climate change on the occurrence and distribution of livestock diseases. *Prev. Vet. Med.* 137, 119–129. <https://doi.org/10.1016/j.prevetmed.2016.11.019>.
- Birhtsa, P.S., Nigam, S.N., Narayanan, A. V., Kareem, K.A., 2012. Potential Economic Benefits from Adoption of Improved Drought-tolerant Groundnut in India. *Agric. Econ. Res. Rev.* 25.
- Bryan, E., Deressa, T.T., Ghebriabou, G.A., Ringler, C., 2009. Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environ. Sci. Policy* 12 (4), 413–426.
- Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., Herrero, M., 2013. Adapting agriculture to climate change in Kenya: household strategies and determinants. *J. Environ. Manage.* 114, 26–35. <https://doi.org/10.1016/j.jenvman.2012.10.036>.
- Byg, A., Salick, J., 2009. Local perspectives on a global phenomenon—climate change in Eastern Tibetan villages. *Glob. Environ. Change* 19 (2), 156–166.
- de Lauwere, G., van Asseldonk, Marcel, van 't Riet, Jonathan, de Hoop, Jitske, ten Pierick, Eric, 2012. Understanding farmers' decisions with regard to animal welfare: The case of changing to group housing for pregnant sows. *Livest. Sci.* 143 (2–3), 151–161.
- Deressa, T.T., Hassan, R.M., Ringler, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *J. Agric. Sci.* 149 (1), 23–31.
- Dilro, G.M., 2013. Impact of off-farm income on agricultural technology adoption intensity and productivity. *Agric. Econ.* 1–15.
- Dublin, Holly T., Ogutu, Joseph O., 2015. Population regulation of African buffalo in the Mara-Serengeti ecosystem. *Wildl. Res.* 42 (5), 382. <https://doi.org/10.1071/WR14205>.
- Faisal, Muhammad, Chunping, Xia, Akhtar, Shoaib, Raza, Muhammad Haseeb, Khan, Muhammad Tariq Iqbal, Ajmal, Muhammad Arslan, 2020. Modeling smallholder livestock herders' intentions to adopt climate smart practices: An extended theory of planned behavior. *Environ. Sci. Pollut. Res.* 27 (31), 39105–39122. <https://doi.org/10.1007/s11356-020-09653-w>.
- Faisal, Muhammad, Chunping, Xia, Abbas, Azhar, Raza, Muhammad Haseeb, Akhtar, Shoaib, Ajmal, Muhammad Arslan, Ali, Abdelrahman, 2021. Do risk perceptions and constraints influence the adoption of climate change practices among small livestock herders in Punjab, Pakistan? *Springer* 28 (32), 43777–43791. <https://doi.org/10.1007/s11356-021-13771-3>.
- Foster, Andrew D., Rosenzweig, Mark R., 2010. Microeconomics of technology adoption. *Annu. Rev. Econom.* 2 (1), 395–424. <https://doi.org/10.1146/annurev.economics.102308.124433>.
- Eckstein, D., Künzel, V., Schäfer, L., Wügel, M., 2019. Global Climate Risk Index 2020. Briefing paper. Germanwatch e.V. Berlin, Germany.
- GOP, 2018. Livestock census Punjab 2018. *Livest. dairy Dev. Dep.*
- Heckman, James, Navarro-Lozano, Salvador, 2004. Using matching, instrumental variables, and control functions to estimate economic choice models. *Rev. Econ. Statist.* 86 (1), 30–57. <https://doi.org/10.1162/003465304323023660>.
- Henry, Beverley, Charmley, Ed, Eckard, Richard, Gaughan, John B., Hegarty, Roger, 2012. Livestock production in a changing climate: adaptation and mitigation research in Australia. *Crop Pasture Sci.* 63 (3), 191. <https://doi.org/10.1071/CP11169>.
- Herrero, M., Thornton, P.K., Notenbaert, A., Msangi, S., Wood, S., Kruska, R., Dixon, J., Bossio, D., Steeg, J. van de, Freeman, H.A., Li, X., Parthasarathy Rao, P., 2012. Drivers of change in crop-livestock systems and their potential impacts on agro-ecosystems services and human wellbeing to 2030: A study commissioned by the CGIAR Systemwide Livestock Programme.
- Hurst, P., 2005. Agricultural workers and their contribution to sustainable agriculture and rural development. October.
- Iheke, O.R., Agodike, W.C., 2016. Analysis of factors influencing the adoption of climate change mitigating measures by smallholder farmers in IMO state, Nigeria. *Analysys* 16.
- Intergovernmental Panel on Climate Change, 2014. Climate Change, Adaptation, and Vulnerability, Organization & Environment. Cambridge University Press Cambridge and New York. https://doi.org/http://ipcc-wg2.gov/AR5/images/uploads/IPCC_WG2AR5_SPM_Approved.pdf.
- Kauppinen, Tiina, Vesala, Kari Mikko, Valros, Anna, 2012. Farmer attitude toward improvement of animal welfare is correlated with piglet production parameters. *Livest. Sci.* 143 (2–3), 142–150.
- Liu, Y., Ruiz-Mejivar, J., Zhang, L., Zhang, J., Swisher, M.E., 2019. Technical training and rice farmers' adoption of low-carbon management practices: the case of soil testing and formulated fertilization technologies in Hubei, China. *J. Clean. Prod.* 226, 454–462. <https://doi.org/10.1016/j.jclepro.2019.04.026>.
- Mango, N., Siziba, S., Makate, C., 2017. The impact of adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. *Agric. Food Secur.* 6, 32.
- Martínez-García, Carlos Galdino, Dorward, Peter, Rehman, Tahir, 2013. Factors influencing adoption of improved grassland management by small-scale dairy farmers in central Mexico and the implications for future research on smallholder adoption in developing countries. *Livest. Sci.* 152 (2–3), 228–238. <https://doi.org/10.1016/j.livsci.2012.10.007>.
- Maskrey, A., Buescher, G., Peduzzi, P., Schaefer, C., 2007. Disaster Risk Reduction: 2007 Global Review. Consult. Ed. Prep. Glob. Platf. Disaster Risk Reduct. First Sess. Geneva, Switz. 5–7.

- Mendoza, Mariapia, 2007. Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh. *Food Policy* 32 (3), 372–393. <https://doi.org/10.1016/j.foodpol.2006.07.003>.
- Mulwa, Chalmers, Marenya, Pawel, Rahut, Dil Bahadur, Kassie, Menale, 2017. Response to climate risks among smallholder farmers in Malawi: a multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Clim. Risk Manage.* 16, 208–221.
- Nablioko, D., Bashaasha, B., Mangheni, M.N., Majaliwa, J.G.M., 2012. Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. *Afr. Crop Sci. J.*
- Nardone, A., Ronchi, B., Lacetera, N., Ranieri, M.S., Bernabucci, U., 2010. Effects of climate changes on animal production and sustainability of livestock systems. *Livest. Sci.* 130 (1–3), 57–69.
- Patz, Jonathan A., Campbell-Lendrum, Diarmid, Holloway, Tracey, Foley, Jonathan A., 2005. Impact of regional climate change on human health. *Nature* 438 (7066), 310–317. <https://doi.org/10.1038/nature04188>.
- Permadi, Dwiko B., Burton, Michael, Pandit, Ram, Race, Digby, Ma, Chunbo, Mendham, Daniel, Hardiyanto, Eko B., 2018. Socio-economic factors affecting the rate of adoption of Acacia plantations by smallholders in Indonesia. *Land Use Policy* 76, 215–223.
- Rahut, D.B., Ali, A., Mottaleb, K.A., 2017. Understanding the determinants of alternate energy options for cooking in the Himalayas: empirical evidence from the Himalayan region of Pakistan. *J. Clean. Prod.* 149, 528–539. <https://doi.org/10.1016/j.jclepro.2017.02.111>.
- Rahut, D.B., Ali, A., 2017. Coping with climate change and its impact on productivity, income, and poverty: evidence from the Himalayan region of Pakistan. *Int. J. Disaster Risk Reduct.* 24, 515–525.
- Rahut, D.B., Ali, A., 2018. Impact of climate-change risk-coping strategies on livestock productivity and household welfare: empirical evidence from Pakistan. *Heliyon* 4 (10), e07977. <https://doi.org/10.1016/j.heliyon.2018.e07977>.
- Raza, Muhammad Haseeb, Abid, Muhammad, Yan, Tingwu, Ali Naqvi, Syed Asif, Akhtar, Shoaib, Faisal, Muhammad, 2019. Understanding farmers' intentions to adopt sustainable crop residue management practices: a structural equation modeling approach. *J. Clean. Prod.* 227, 613–623.
- Rigolot, C., de Voil, P., Doumchamps, S., Prestwidge, D., Van Wijk, M., Thornton, P.K., Rodriguez, D., Henderson, B., Medina, D., Herrero, M., 2017. Interactions between intervention packages, climatic risk, climate change and food security in mixed crop-livestock systems in Burkina Faso. *Agric. Syst.* 151, 217–224.
- Rosegrant, M.W., Fernandez, M., Sinha, A., Alder, J., Ahammad, H., Fraiture, C. de, Elkhour, B., Fonseca, J., Huang, J., Koyama, O., Omerzine, A.M., Pingali, P., Ramirez, R., Ringler, C., Robinson, S., Thornton, P.K., van Vuuren, D., Yana-Shapiro, H., 2009. Looking into the future for agriculture and AKST (Agricultural Knowledge Science and Technology), in: *Agriculture at a Crossroads*, Global Report. pp. 307–376.
- Seerapu, Sandeep Reddy, Kancharana, Ananda Rao, Chappidi, Venkata Seshiah, Bandi, Eswara Rao, 2015. Effect of microclimate alteration on milk production and composition in Murrah buffaloes. *Vet. world* 8 (12), 1444–1452.
- Senger, Igor, Borges, João Augusto Rossi, Machado, João Armando Desimon, 2017. Using structural equation modeling to identify the psychological factors influencing dairy farmers' intention to diversify agricultural production. *Livest. Sci.* 203, 97–105.
- Simtowe, F., Zeller, M., 2007. The Impact of Access to Credit on the Adoption of hybrid maize in Malawi: An Empirical test of an Agricultural Household Model under credit market failure, AAAI Conference.
- St-Pierre, N.R., Cobanov, B., Schnitzky, G., 2003. Economic losses from heat stress by US livestock industries1. *J. Dairy Sci.* 86, E52–E77.
- Tan, Emrullah, 2014. Human capital theory: a holistic criticism. *Rev. Educ. Res.* 84 (3), 411–445. <https://doi.org/10.3102/0034654314532696>.
- Tesema, Y.A., Joerin, J., Patt, A., 2018. Factors affecting smallholder farmers' adaptation to climate change through non-technological adjustments. *Environ. Dev.* 25, 33–42. <https://doi.org/10.1016/j.environdev.2017.11.001>.
- Thornton, Philip K., 2010. Livestock production: recent trends, future prospects. *Philos. Trans. R. Soc. London B Biol. Sci.* 365 (1554), 2853–2867.
- Thornton, Philip K., Ericksen, Polly J., Herrero, Mario, Challinor, Andrew J., 2014. Climate variability and vulnerability to climate change: a review. *Glob. Chang. Biol.* 20 (11), 3313–3328.
- Thornton, P.K., Boone, R.B., Ramirez-Villegas, J., 2015. Climate Change Impacts on Livestock CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Working Paper.
- Thornton, Philip K., Gerber, Pierre J., 2010. Climate change and the growth of the livestock sector in developing countries. *Mitig. Adapt. Strateg. Glob. Chang.* 15 (2), 169–184.
- Thornton, Philip K., Herrero, Mario, 2015. Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. *Nat. Clim. Change* 5 (9), 830–836.
- Thornton, P.K., van de Steeg, J., Notenbaert, A., Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries: a review of what we know and what we need to know. *Agric. Syst.* 101 (3), 113–127.
- Uaiene, R.N., 2008. Determinants of agricultural technical efficiency and technology adoption in Mozambique. Dissertation. Purdue University. Discuss. Pap.
- Yu, W., 2010. Climate Change Risks and Food Security in Bangladesh, Climate Change Risks and Food Security in Bangladesh. Routledge. <https://doi.org/10.4324/9781849776387>.

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



**Int. J. Environ. Res. Public Health, Volume 18, Issue 20
(October-2 2021) – 442 articles**



Cover Story (view full-size image): The safety of tap water is an important condition for consumers to drink it. Adequate information for consumers on aspects of safety should therefore be included in the roadmap toward the UN SDG 6 on safe drinking water for all. This paper studies consumers' information needs regarding emerging contaminants in drinking water using a mental model approach for the development of targeted risk communications. As most consumers expect safe drinking water to be free of contamination, communication on emerging contaminants may increase concerns. The results of a survey among 510 participants showed that communication strategies better tailored to consumers' information needs result in smaller increases in risk perception compared with existing strategies. [View this paper](#)

- Issues are regarded as officially published after their release is announced to the table of contents alert mailing list.
- You may sign up for e-mail alerts to receive table of contents of newly released issues.
- PDF is the official format for papers published in both, html and pdf forms. To view the papers in pdf format, click on the "PDF Full-text" link, and use the free Adobe Reader to open them.

Order results	Result format	Section
Publication Date ▾	Normal ▾	Climate Change ▾

Show export options ▾

[Open Access](#) [Article](#) 27 pages, 3812 KB

Associating Land Cover Changes with Patterns of Incidences of Climate-Sensitive Infections: An Example on Tick-Borne Diseases in the Nordic Area

by [Didier G. Leblond](#), [Helena Bylund](#), [Christer Björkman](#), [Miroslav Tokarevich](#), [Tomas Thierfelder](#), [Birgitta Ewingdottir](#) and [Shawn Gaudin](#)

Int. J. Environ. Res. Public Health 2021, 18(23), 10063. <https://doi.org/10.3390/ijerph182310063> - 19 Oct 2021

Cited by 8 | Viewed by 2347

Abstract: Some of the climate-sensitive infections (CSIs) affecting humans are zoonotic vector-borne diseases, such as Lyme borreliosis (LB) and tick-borne encephalitis (TBE), mostly linked to various species of ticks as vectors. Due to climate change, the geographical distribution of tick species, their hosts, and [...] [Read more](#)

(This article belongs to the Special Issue Climate-Change Effects on the Epidemiology of Infectious Diseases and the Impacts on Northern Societies)

[► Show Figures](#)

[Open Access](#) [Review](#) 17 pages, 1021 KB

Climate Change and Child Health Inequality: A Review of Reviews

by [Emmanuel Arpin](#), [Karl Gauthier](#), [Meghan Kerr](#), [Anders Hjert](#), [Angela Mashford-Pringle](#), [Alejo Berres](#), [Luis Rajmil](#), [Irfi Chopra](#) and [Michiel Spencer](#)

Int. J. Environ. Res. Public Health 2021, 18(23), 10066. <https://doi.org/10.3390/ijerph182310066> - 17 Oct 2021

Cited by 7 | Viewed by 4964

Abstract: There is growing evidence on the observed and expected consequences of climate change on population health worldwide. There is limited understanding of its consequences for child health inequalities, between and within countries. To examine these consequences and categorize the state of knowledge in [...] [Read more](#)

(This article belongs to the Special Issue Climate-Driven Health Impacts)

[► Show Figures](#)

[Open Access](#) [Article](#) 16 pages, 1400 KB

Utilizing Social Media for Information Dispersal during Local Disasters: The Communication Hub Framework for Local Emergency Management

by [Dianne Mitchem](#), [Morgan Taylor](#) and [Curtis Harris](#)

Int. J. Environ. Res. Public Health 2021, 18(23), 10704. <https://doi.org/10.3390/ijerph182310704> - 14 Oct 2021

Cited by 19 | Viewed by 2508

Abstract: In today's society, the use of social media has increased the public's desire to receive information quickly and to be able to interact with communications. During a disaster, the trend to turn to social media for information has risen in popularity. Society's reliance [...] [Read more](#)

(This article belongs to the Special Issue Community Participation in Disaster Risk Reduction: Perspectives, Methodologies and Evaluations)

[► Show Figures](#)

[Open Access](#) [Article](#) 21 pages, 3380 KB

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

by [Muhammad Faheem](#), [Azhar Abbas](#), [Yi Cai](#), [Abdulahman A.S.](#), [Muhammad Amir Shauqat](#), [Shoaib Akhtar](#), [Muhammad Haseeb Raza](#), [Muhammad Anwar Ajmal](#), [Chunping Xia](#), [Syed Abdul Sattar](#) and [Zahira Batool](#)

Int. J. Environ. Res. Public Health 2021, 18(23), 10771. <https://doi.org/10.3390/ijerph182310771> - 14 Oct 2021

Cited by 4 | Viewed by 3236

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 [...] [Read more](#)

(This article belongs to the Special Issue Climate Change and Infectious Diseases Risks)

[► Show Figures](#)



Article

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

Muhammad Faisal ^{1,2}, Azhar Abbas ², Yi Cai ^{3,*}, Abdelrahman Ali ^{1,4}, Muhammad Amir Shahzad ¹, Shoaib Akhtar ⁵, Muhammad Haseeb Raza ⁶, Muhammad Arslan Ajmal ⁷, Chunping Xia ¹, Syed Abdul Sattar ⁸ and Zahira Batool ⁹

¹ College of Economics and Management, Huazhong Agricultural University, Wuhan 430070, China; faisalgurmani@gmail.com (M.F.); aaa31@fayoum.edu.eg (A.A.); sivia.amir@gmail.com (M.A.S.); xcp@mail.hzau.edu.cn (C.X.)

² Institute of Agricultural and Resource Economics, University of Agriculture Faisalabad, Faisalabad 38000, Pakistan; azhar.abbas@uaf.edu.pk

³ Research Center for Green Development of Agriculture, Digital Countryside Research Institute, College of Economics and Management, South China Agricultural University, Guangzhou 510640, China

⁴ Department of Agricultural Economics, Fayoum University, Fayoum 63514, Egypt

⁵ Centre of Excellence for Olive Research and Training (CEFORT), Barani Agricultural Research Institute, Chakwal 48800, Pakistan; shoaibakhtar1799@gmail.com

⁶ Institute of Business Management Sciences, University of Agriculture Faisalabad, Faisalabad 38000, Pakistan; haseebzvi00@yahoo.com

⁷ Department of Economics, Government College University, Faisalabad 38000, Pakistan; arslan.gogo7@gmail.com

⁸ Agriculture Research Institute, District Kharan, Balochistan 94100, Pakistan; syedabdulsattar1975@gmail.com

⁹ Department of Sociology, Government College University, Faisalabad 38000, Pakistan; batoolazam@hotmail.com

* Correspondence: caiyi@scau.edu.cn

Citation: Faisal, M.; Abbas, A.; Cai, Y.; Ali, A.; Shahzad, M.A.; Akhtar, S.; Haseeb Raza, M.; Ajmal, M.A.; Xia, C.; Sattar, S.A.; et al. Perceptions, Vulnerability and Adaptation Strategies for Mitigating Climate Change Effects among Small Livestock Herders in Punjab, Pakistan. *Int. J. Environ. Res. Public Health* **2021**, *18*, 10771. <https://doi.org/10.3390/ijerph182010771>

Received: 30 August 2021

Accepted: 29 September 2021

Published: 14 October 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

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].

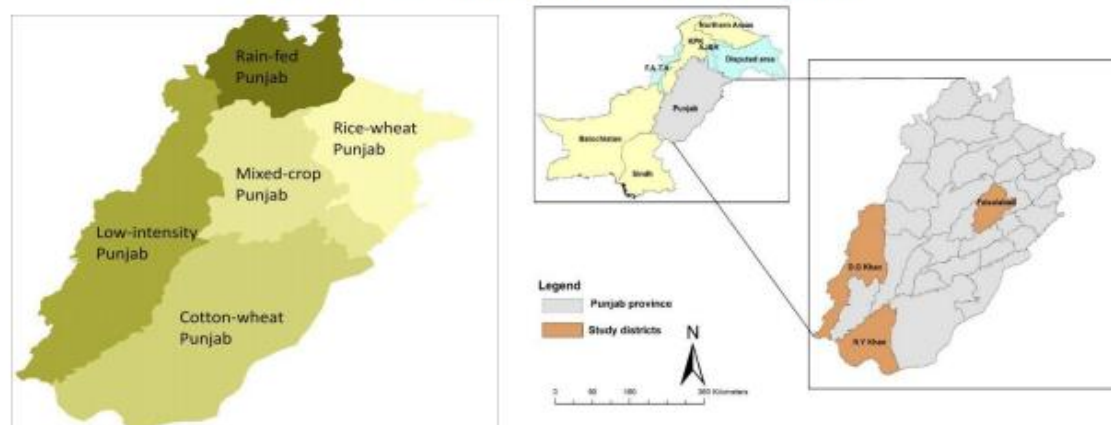


Figure 1. Map categorizing the agro-ecological zones of Punjab and the study area.

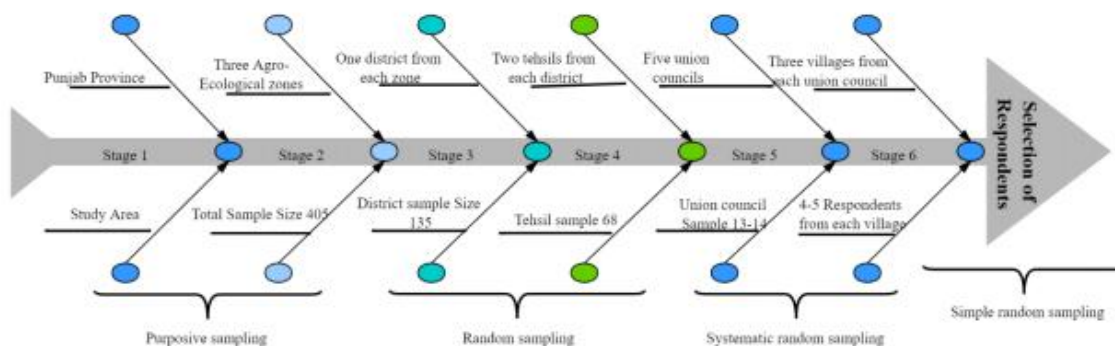


Figure 2. Sampling strategy.

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

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:

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

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):

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

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), β_0 = constant, β_i = coefficient of independent variables, X_i = explanatory variables, and ε_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 Liquified 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.

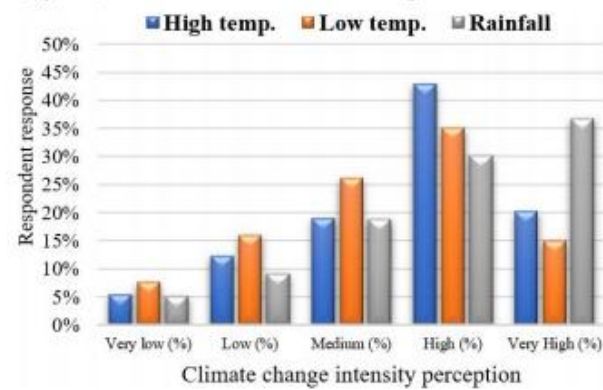


Figure 3. Respondents' stated perceptions about high/low temperature and rainfall during the past 10 years.

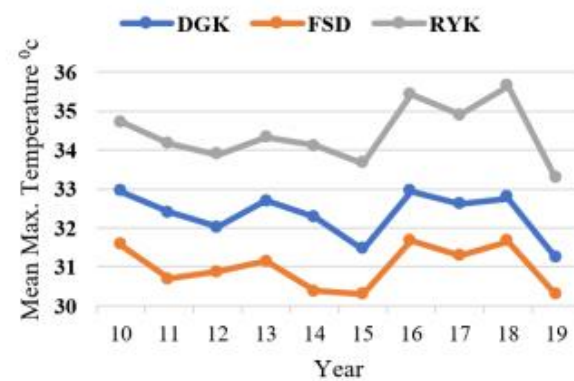


Figure 4. Maximum temperature (mean) of study locations (2010–2019).

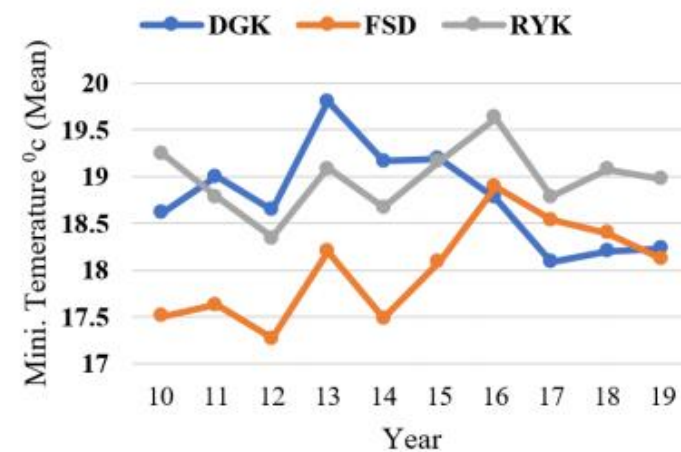


Figure 5. Minimum temperature (mean) of study locations (2010–2019).

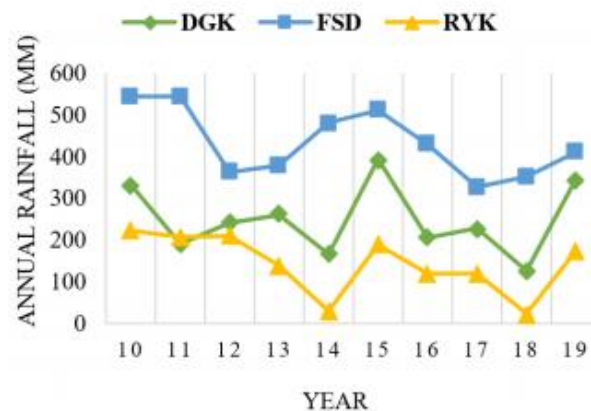


Figure 6. Annual rainfall in the study locations (2010–2019).

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	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
			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)	0.561	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	0.496	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			0.540	0.489	0.207
	SEN14	Household members less than 15 years	0.126	0.330	0.144
Adaptation Efficacy	SEN15	Household members greater than 65 years	0.136	0.130	0.141
			0.135	0.230	0.142
Self-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
Economic Capability			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
Human Resource Capability	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
Institutional 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
Overall livelihood vulnerability index (LVI) *			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
Overall livelihood vulnerability index (LVI) *	AC9	Livestock experience	0.405	0.351	0.446
			0.302	0.314	0.475
	AC10	Distance to reach the road	0.251	0.257	0.233
Overall livelihood vulnerability index (LVI) *	AC11	Distance to market	0.304	0.378	0.428
	AC12	Basic repair facilities available in village	0.286	0.319	0.770
			0.277	0.351	0.477
Overall livelihood vulnerability index (LVI) *			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).

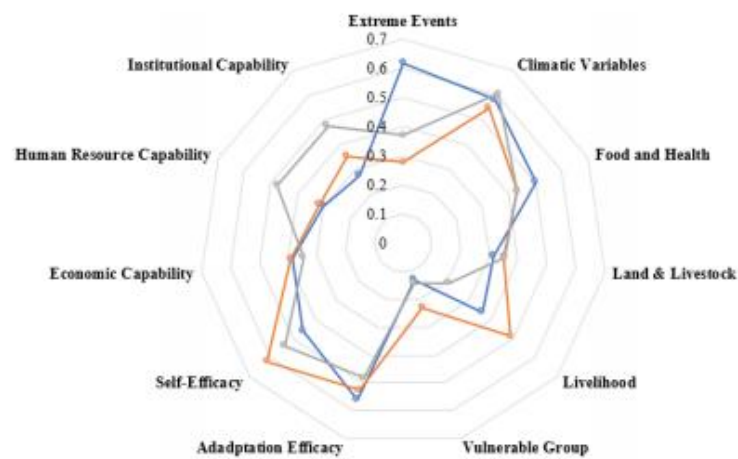


Figure 7. Spider diagram of vulnerability based on major components of LVI of the study area.

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).

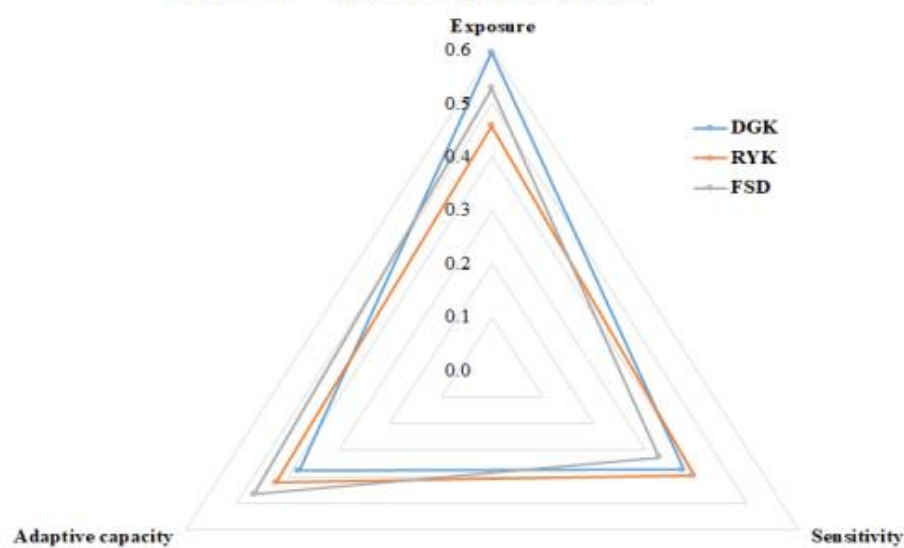


Figure 8. LVI-IPCC contributing factors of the three agro-ecological zones.

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 *** (0.245)	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 (0.395)	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.

Author Contributions: Conceptualization, M.F., A.A. (Azhar Abbas) and A.A. (Abdelrahman Ali); methodology, M.F.; software, M.F.; validation, M.F., A.A. (Abdelrahman Ali), C.X.; formal analysis, M.A.S.; investigation, M.A.A.; resources, M.F.; data curation, M.H.R.; writing—original draft preparation, M.F.; writing—review and editing, M.F., A.A. (Azhar Abbas), S.A., Y.C., S.A.S., Z.B.; visualization, Y.C.; supervision, C.X., A.A. (Azhar Abbas), Y.C.; project administration, Y.C.; funding acquisition, Y.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the special funds for the development of high level universities (4700-220140), the Youth Project of Guangdong Provincial Department of Education (2020WQNCX006), and the Social Science Fund of Guangdong (GD21YYJ06).

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.

Conflicts of Interest: The authors declare no conflict of interest with respect to the research authorship and publication of this article.

References

1. Fahad, S.; Wang, J. Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. *Land Use Policy* **2018**, *79*, 301–309. [CrossRef]
2. IPCC Impacts, Adaptation, and Vulnerability: Contribution of working group II to the fifth assessment report of the Intergovernmental Panel on Climate Change. *Intergov. Panel Clim. Chang.* **2014**, 1–44. Available online: <https://epic.awi.de/id/eprint/37530/> (accessed on 15 December 2020).
3. Kohler, T.; Maselli, D. *Mountains and Climate Change—From Understanding to Action*; Geographica Bernensia: Bern, Switzerland, 2009; ISBN 9783905835168.
4. Dendir, Z.; Simane, B. Livelihood vulnerability to climate variability and change in different agroecological zones of Gurage Administrative Zone, Ethiopia. *Prog. Disaster Sci.* **2019**, *3*, 100035. [CrossRef]
5. Jamshidi, O.; Asadi, A.; Kalantari, K.; Azadi, H.; Scheffran, J. Vulnerability to climate change of smallholder farmers in the Hamadan province, Iran. *Clim. Risk Manag.* **2019**, *23*, 146–159. [CrossRef]
6. Faisal, M.; Chunping, X.; Akhtar, S.; Raza, M.H.; Khan, M.T.I.; Ajmal, M.A. Modeling smallholder livestock herders' intentions to adopt climate smart practices: An extended theory of planned behavior. *Environ. Sci. Pollut. Res.* **2020**, *27*, 39105–39122. [CrossRef]
7. Lindoso, D.P.; Rocha, J.D.; Debortoli, N.; Parente, I.C.I.; Eiró, F.; Filho, S.R. Indicators for assessing the vulnerability of smallholder farming to climate change: The case of Brazil's semi-arid northeastern region. *Int. Policy Cent. Incl. Growth* **2012**. Available online: <https://research.rug.nl/en/publications/indicators-for-assessing-the-vulnerability-of-smallholder-farming> (accessed on 15 December 2020).
8. Omerkhil, N.; Chand, T.; Valente, D.; Alatalo, J.M.; Pandey, R. Climate change vulnerability and adaptation strategies for smallholder farmers in Yangi Qala District, Takhar, Afghanistan. *Ecol. Indic.* **2020**, *110*, 105863. [CrossRef]
9. Alam, M.M.; Siwar, C.; Talib, B.A.; Wahid, A.N.M. Climatic changes and vulnerability of household food accessibility: A study on Malaysian East Coast Economic Region. *Int. J. Clim. Chang. Strateg. Manag.* **2017**, *9*, 387–401. [CrossRef]
10. Fang, Z.; Cao, C. *The State of Food Security and Nutrition in the World 2019. Building Climate Resilience for Food Security and Nutrition*; FAO: Rome, Italy, 2019; Volume 7, ISBN 9789251315705.

11. Faisal, M.; Abbas, A.; Chunping, X.; Haseeb Raza, M.; Akhtar, S.; Arslan Ajmal, M.; Mushtaq, Z.; Cai, Y. Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty. *Clim. Risk Manag.* **2021**, *34*, 100358. [\[CrossRef\]](#)
12. Harvey, C.A.; Rakotobe, Z.L.; Rao, N.S.; Dave, R.; Razafimahatratra, H.; Rabarijohn, R.H.; Rajaofara, H.; MacKinnon, J.L. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philos. Trans. R. Soc. B Biol. Sci.* **2014**, *369*, 20130089. [\[CrossRef\]](#)
13. Thornton, P.K.; Ericksen, P.J.; Herrero, M.; Challinor, A.J. Climate variability and vulnerability to climate change: A review. *Glob. Chang. Biol.* **2014**, *20*, 3313–3328. [\[CrossRef\]](#)
14. Karimi, V.; Karami, E.; Keshavarz, M. Vulnerability and adaptation of livestock producers to climate variability and change. *Rangel. Ecol. Manag.* **2018**, *71*, 175–184. [\[CrossRef\]](#)
15. Castells-Quintana, D.; del Pilar Lopez-Urbe, M.; McDermott, T.K.J. Adaptation to climate change: A review through a development economics lens. *World Dev.* **2018**, *104*, 183–196. [\[CrossRef\]](#)
16. Ahmad, M.I.; Ma, H. Climate change and livelihood vulnerability in mixed crop-livestock areas: The case of Province Punjab, Pakistan. *Sustainability* **2020**, *12*, 586. [\[CrossRef\]](#)
17. Hasan, M.K.; Kumar, L. Comparison between meteorological data and farmer perceptions of climate change and vulnerability in relation to adaptation. *J. Environ. Manag.* **2019**, *237*, 54–62. [\[CrossRef\]](#)
18. Weber, E.U. What shapes perceptions of climate change? *Wiley Interdiscip. Rev. Clim. Chang.* **2010**, *1*, 332–342. [\[CrossRef\]](#)
19. Abidoye, B.O.; Kurukulasuriya, P.; Mendelsohn, R. South-East Asian farmer perceptions of climate change. *Clim. Chang. Econ.* **2017**, *8*, 1740006. [\[CrossRef\]](#)
20. Elum, Z.A.; Modise, D.M.; Marr, A. Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa. *Clim. Risk Manag.* **2017**, *16*, 246–257. [\[CrossRef\]](#)
21. Kibue, G.W.; Liu, X.; Zheng, J.; Zhang, X.; Pan, G.; Li, L.; Han, X. Farmers' Perceptions of Climate Variability and Factors Influencing Adaptation: Evidence from Anhui and Jiangsu, China. *Environ. Manag.* **2016**, *57*, 976–986. [\[CrossRef\]](#)
22. Mertz, O.; Mbow, C.; Reenberg, A.; Diouf, A. Farmers' perceptions of climate change and agricultural adaptation strategies in rural sahel. *Environ. Manag.* **2009**, *43*, 804–816. [\[CrossRef\]](#)
23. Mubiru, D.N.; Radeny, M.; Kyazze, F.B.; Zziwa, A.; Lwasa, J.; Kinyangi, J.; Mungai, C. Climate trends, risks and coping strategies in smallholder farming systems in Uganda. *Clim. Risk Manag.* **2018**, *22*, 4–21. [\[CrossRef\]](#)
24. Mahmood, N.; Arshad, M.; Kaechele, H.; Shahzad, M.F.; Ullah, A.; Mueller, K. Fatalism, climate resiliency training and farmers' adaptation responses: Implications for sustainable rainfed-wheat production in Pakistan. *Sustainability* **2020**, *12*, 1650. [\[CrossRef\]](#)
25. Leiserowitz, A. Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Clim. Chang.* **2006**, *77*, 45–72. [\[CrossRef\]](#)
26. Li, S.; Juhász-Horváth, L.; Harrison, P.A.; Pintér, L.; Rounsevell, M.D.A. Relating farmer's perceptions of climate change risk to adaptation behaviour in Hungary. *J. Environ. Manag.* **2017**, *185*, 21–30. [\[CrossRef\]](#)
27. Maddison, D.; Bank, T.W. *The Perception of and Adaptation to Climate Change in Africa*, Policy Research Working Paper 4308; Policy Research Working Papers; The World Bank: Washington, DC, USA, 2007.
28. Thornton, P.K.; van de Steeg, J.; Notenbaert, A.; Herrero, M. The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know. *Agric. Syst.* **2009**, *101*, 113–127. [\[CrossRef\]](#)
29. Thi Lan Huong, N.; Shun Bo, Y.; Fahad, S. Farmers' perception, awareness and adaptation to climate change: Evidence from northwest Vietnam. *Int. J. Clim. Chang. Strateg. Manag.* **2017**, *9*, 555–576. [\[CrossRef\]](#)
30. Kabir, M.I.; Rahman, M.B.; Smith, W.; Lusha, M.A.F.; Azim, S.; Milton, A.H. Knowledge and perception about climate change and human health: Findings from a baseline survey among vulnerable communities in Bangladesh. *BMC Public Health* **2016**, *16*, 266. [\[CrossRef\]](#)
31. Qasim, S.; Nawaz Khan, A.; Prasad Shrestha, R.; Qasim, M. Risk perception of the people in the flood prone Khyber Pukhthunkhwa province of Pakistan. *Int. J. Disaster Risk Reduct.* **2015**, *14*, 373–378. [\[CrossRef\]](#)
32. Hassan, R.; Nhemachena, C. Determinants of African Farmers' Strategies for Adapting to Climate Change: Multinomial Choice Analysis. *Afri. J. Agric. Res. Eco.* **2008**, *2*, 22.
33. Shameem, M.I.M.; Momtaz, S.; Kiem, A.S. Local perceptions of and adaptation to climate variability and change: The case of shrimp farming communities in the coastal region of Bangladesh. *Clim. Chang.* **2015**, *133*, 253–266. [\[CrossRef\]](#)
34. Tessema, Y.A.; Joerin, J.; Patt, A. Factors affecting smallholder farmers' adaptation to climate change through non-technological adjustments. *Environ. Dev.* **2018**, *25*, 33–42. [\[CrossRef\]](#)
35. Huong, N.T.L.; Yao, S.; Fahad, S. Assessing household livelihood vulnerability to climate change: The case of Northwest Vietnam. *Hum. Ecol. Risk Assess.* **2019**, *25*, 1157–1175. [\[CrossRef\]](#)
36. Venkateswarlu, B.; Shanker, A.K. Climate change and agriculture: Adaptation and mitigation strategies. *Indian J. Agron.* **2009**, *54*, 226–230.
37. Abid, M.; Schilling, J.; Scheffran, J.; Zulfikar, F. Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Sci. Total Environ.* **2016**, *547*, 447–460. [\[CrossRef\]](#)
38. Fussler, H.M.; Klein, R.J.T. Climate change vulnerability assessments: An evolution of conceptual thinking. *Clim. Chang.* **2006**, *75*, 301–329. [\[CrossRef\]](#)

39. Gallopín, G.C. Linkages between Vulnerability, Resilience, and Adaptive Capacity. *Glob. Environ. Chang.* **2006**, *16*, 293–303. [\[CrossRef\]](#)
40. Hahn, M.B.; Riederer, A.M.; Foster, S.O. The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Glob. Environ. Chang.* **2009**, *19*, 74–88. [\[CrossRef\]](#)
41. Kelly, P.M.; Adger, W.N. Theory and practice in assessing vulnerability to climate change and facilitating adaptation. *Clim. Chang.* **2000**, *47*, 325–352. [\[CrossRef\]](#)
42. Fisher, E.; Attah, R.; Barca, V.; O'Brien, C.; Brook, S.; Holland, J.; Kardan, A.; Pavanello, S.; Pozarny, P. The livelihood impacts of cash transfers in sub-Saharan Africa: Beneficiary perspectives from six countries. *World Dev.* **2017**, *99*, 299–319. [\[CrossRef\]](#)
43. Salik, K.M.; Jahangir, S.; Zahdi, W.Z.; Hasson, S. Climate change vulnerability and adaptation options for the coastal communities of Pakistan. *Ocean. Coast. Manag.* **2015**, *112*, 61–73. [\[CrossRef\]](#)
44. Reed, M.S.; Podesta, G.; Fazey, I.; Geeson, N.; Hessel, R.; Hubacek, K.; Letson, D.; Nainggolan, D.; Prell, C.; Rickenbach, M.G.; et al. Combining analytical frameworks to assess livelihood vulnerability to climate change and analyse adaptation options. *Ecol. Econ.* **2013**, *94*, 66–77. [\[CrossRef\]](#)
45. Schilling, J.; Freier, K.P.; Hertig, E.; Scheffran, J. Climate change, vulnerability and adaptation in North Africa with focus on Morocco. *Agric. Ecosyst. Environ.* **2012**, *156*, 12–26. [\[CrossRef\]](#)
46. Schneider, S.; Azar, C.; Baethgen, W.; Hope, C.; Moss, R.; Leary, N.; Richels, R.; Ypersele, J.-P.; Kuntz-Duriseti, K.; Jones, R. Overview of Impacts, Adaptation and Vulnerability to Climate Change. In *Climate Change 2001: Impacts, Adaptation, and Vulnerability*; IDEAM: Bogotá, Colombia, 2001; pp. 75–103.
47. Fellmann, T. The Assessment of Climate Change-Related Vulnerability in the Agricultural Sector: Reviewing Conceptual Frameworks. In *Building Resilience for Adaptation to Climate Change in the Agriculture Sector*; FAO: Rome, Italy, 2012; Volume 23, pp. 37–62.
48. Turner, B.L.; Kasperson, R.E.; Matson, P.A.; McCarthy, J.J.; Corell, R.W.; Christensen, L.; Eckley, N.; Kasperson, J.X.; Luers, A.; Martello, M.L.; et al. A framework for vulnerability analysis in sustainability science. *Proc. Natl. Acad. Sci. USA* **2003**, *100*, 8074–8079. [\[CrossRef\]](#)
49. Wang, J.; Brown, D.G.; Agrawal, A. Climate adaptation, local institutions, and rural livelihoods: A comparative study of herder communities in Mongolia and Inner Mongolia, China. *Glob. Environ. Chang.* **2013**, *23*, 1673–1683. [\[CrossRef\]](#)
50. Brooks, N.; Adger, W.N.; Kelly, P.M. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Glob. Environ. Chang.* **2005**, *15*, 151–163. [\[CrossRef\]](#)
51. Nakicenovic, N.; Alcamo, J.; Davis, G.; Vries, B.; Fenhann, J. Lawrence Berkeley National Laboratory Recent Work. In *Special Report on Emissions Scenarios*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2000; ISBN 92-9169-113-5.
52. Smit, B.; Wandel, J. Adaptation, adaptive capacity and vulnerability. *Glob. Environ. Chang.* **2006**, *16*, 282–292. [\[CrossRef\]](#)
53. Gupta, A.K.; Negi, M.; Nandy, S.; Kumar, M.; Singh, V.; Valente, D.; Petrosillo, L.; Pandey, R. Mapping socio-environmental vulnerability to climate change in different altitude zones in the Indian Himalayas. *Ecol. Indic.* **2020**, *109*, 105787. [\[CrossRef\]](#)
54. Weis, S.W.M.; Agostini, V.N.; Roth, L.M.; Gilmer, B.; Schill, S.R.; Knowles, J.E.; Blyther, R. Assessing vulnerability: An integrated approach for mapping adaptive capacity, sensitivity, and exposure. *Clim. Chang.* **2016**, *136*, 615–629. [\[CrossRef\]](#)
55. Adu, D.T.; Kuwornu, J.K.M.; Anim-Somuah, H.; Sasaki, N. Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana. *Kasetsart J. Soc. Sci.* **2018**, *39*, 22–32. [\[CrossRef\]](#)
56. Niles, M.T.; Brown, M.; Dynes, R. Farmer's intended and actual adoption of climate change mitigation and adaptation strategies. *Clim. Chang.* **2016**, *135*, 277–295. [\[CrossRef\]](#)
57. Byrne, T.R. *Household Adaptive Capacity and Current Vulnerability to Future Climate Change in Rural Nicaragua*; University of Lethbridge: Lethbridge, AB, Canada, 2014.
58. Gizachew, L.; Shimelis, A. Analysis and Mapping of Climate Change Risk and Vulnerability in Central Rift Valley of Ethiopia. *Afr. Crop. Sci. J.* **2014**, *22*, 807–818.
59. Niles, M.T.; Mueller, N.D. Farmer perceptions of climate change: Associations with observed temperature and precipitation trends, irrigation, and climate beliefs. *Glob. Environ. Chang.* **2016**, *39*, 133–142. [\[CrossRef\]](#)
60. Pearson, L.J.; Nelson, R.; Crimp, S.; Langridge, J. Interpretive review of conceptual frameworks and research models that inform Australia's agricultural vulnerability to climate change. *Environ. Model. Softw.* **2011**, *26*, 113–123. [\[CrossRef\]](#)
61. Chinwendu, O.G.; Sadiku, S.O.E.; Okhimamhe, A.O.; Echie, J. Households Vulnerability and Adaptation to Climate Variability Induced Water Stress on Downstream Kaduna River Basin. *Am. J. Clim. Chang.* **2017**, *06*, 247–267. [\[CrossRef\]](#)
62. Thornton, P.K.; Herrero, M. Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. *Nat. Clim. Chang.* **2015**, *5*, 830. [\[CrossRef\]](#)
63. Raza, M.H.; Abid, M.; Yan, T.; Naqvi, S.A.A.; Akhtar, S.; Faisal, M. Understanding farmers' intentions to adopt sustainable crop residue management practices: A structural equation modeling approach. *J. Clean. Prod.* **2019**, *227*, 613–623. [\[CrossRef\]](#)
64. Sarker, M.N.I.; Wu, M.; Alam, G.M.M.; Shouse, R.C. Life in riverine islands in Bangladesh: Local adaptation strategies of climate vulnerable riverine island dwellers for livelihood resilience. *Land Use Policy* **2020**, *94*, 104574. [\[CrossRef\]](#)
65. Akanda, M.G.R.; Howlader, M.S. Coastal Farmers' Perception of Climate Change Effects on Agriculture at Galachipa Upazila under Patuakhali District of Bangladesh. *Glob. J. Sci. Front. Res. Agric. Vet.* **2015**, *15*, 31–39.

66. Hunt, A.; Watkiss, P. Climate change impacts and adaptation in cities: A review of the literature. *Clim. Chang.* **2011**, *104*, 13–49. [\[CrossRef\]](#)
67. Faisal, M.; Chunping, X.; Akhtar, S.; Raza, M.H.; Nazir, A.; Mushtaq, Z.; Ajmal, M.A. Economic Analysis and Production Efficiency of Dark Sun Cured Rustica Tobacco Production A Case Study of Punjab, Pakistan. *J. Soc. Sci. Hum. Stud.* **2018**, *4*, 7–14.
68. Faisal, M.; Akhtar, S.; Raza, M.H.; Rehman, A.; Chunping, X.; Mushtaq, Z.; Ajmal, M.A.; Hussain, A. Assessing the Factors Affecting the Yield of Dark Sun Cured Rustica Tobacco. A Case Study of Rajanpur, Punjab. *J. Soc. Sci. Hum. Stud.* **2018**, *4*, 1–6.
69. Shahzad, M.A.; Qing, P.; Rizwan, M.; Razzaq, A.; Faisal, M. COVID-19 Pandemic, Determinants of Food Insecurity, and Household Mitigation Measures: A Case Study of Punjab, Pakistan. *Healthcare* **2021**, *9*, 621. [\[CrossRef\]](#)
70. Faisal, M.; Chunping, X.; Abbas, A.; Raza, M.H.; Akhtar, S.; Ajmal, M.A.; Ali, A. Do risk perceptions and constraints influence the adoption of climate change practices among small livestock herders in Punjab, Pakistan? *Environ. Sci. Pollut. Res.* **2021**, *28*, 43777–43791. [\[CrossRef\]](#)
71. Ali, A. Impact of climate-change risk-coping strategies on livestock productivity and household welfare: Empirical evidence from Pakistan. *Heliyon* **2018**, *4*, e00797.
72. Abid, M.; Scheffran, J.; Schneider, U.A.; Ashfaq, M. Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab province, Pakistan. *Earth Syst. Dynam.* **2015**, *6*, 225–243. [\[CrossRef\]](#)
73. Bastakoti, R.C.; Gupta, J.; Babel, M.S.; van Dijk, M.P. Climate risks and adaptation strategies in the Lower Mekong River basin. *Reg. Environ. Chang.* **2014**, *14*, 207–219. [\[CrossRef\]](#)
74. Akhtar, S.; Li, G.C.; Nazir, A.; Razzaq, A.; Ullah, R.; Faisal, M.; Naseer, M.A.U.R.; Raza, M.H. Maize production under risk: The simultaneous adoption of off-farm income diversification and agricultural credit to manage risk. *J. Integr. Agric.* **2019**, *18*, 460–470. [\[CrossRef\]](#)
75. Akhtar, S.; Li, G.C.; Ullah, R.; Nazir, A.; Iqbal, M.A.; Raza, M.H.; Iqbal, N.; Faisal, M. Factors influencing hybrid maize farmers' risk attitudes and their perceptions in Punjab Province, Pakistan. *J. Integr. Agric.* **2018**, *17*, 1454–1462. [\[CrossRef\]](#)
76. Mulwa, C.; Marenja, P.; Kassie, M. Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Clim. Risk Manag.* **2017**, *16*, 208–221. [\[CrossRef\]](#)
77. Tan, E. Human Capital Theory: A Holistic Criticism. *Rev. Educ. Res.* **2014**, *84*, 411–445. [\[CrossRef\]](#)
78. Permadi, D.B.; Burton, M.; Pandit, R.; Race, D.; Ma, C.; Mendham, D.; Hardiyanto, E.B. Socio-economic factors affecting the rate of adoption of Acacia plantations by smallholders in Indonesia. *Land Use Policy* **2018**, *76*, 215–223. [\[CrossRef\]](#)
79. Ali, A. Coping with climate change and its impact on productivity, income, and poverty: Evidence from the Himalayan region of Pakistan. *Int. J. Disaster Risk Reduct.* **2017**, *24*, 515–525.
80. Khandker, S.R.; Barnes, D.F.; Samad, H.A. Are the energy poor also income poor? Evidence from India. *Energy Policy* **2012**, *47*, 1–12. [\[CrossRef\]](#)
81. Deressa, T.T.; Hassan, R.M.; Ringler, C. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *J. Agric. Sci.* **2011**, *149*, 23–31. [\[CrossRef\]](#)
82. Ahmed, Z.; Guha, G.S.; Shew, A.M.; Alam, G.M.M. Climate change risk perceptions and agricultural adaptation strategies in vulnerable riverine char islands of Bangladesh. *Land Use Policy* **2021**, *103*, 105295. [\[CrossRef\]](#)
83. Shah, A.A.; Ye, J.; Abid, M.; Khan, J.; Amir, S.M. Flood hazards: Household vulnerability and resilience in disaster-prone districts of Khyber Pakhtunkhwa province, Pakistan. *Nat. Hazards* **2018**, *93*, 147–165. [\[CrossRef\]](#)
84. Rust, J.M. The impact of climate change on extensive and intensive livestock production systems. *Anim. Front.* **2019**, *9*, 20–25. [\[CrossRef\]](#) [\[PubMed\]](#)
85. Rivera-Ferre, M.G.; López-i-Gelats, F.; Howden, M.; Smith, P.; Morton, J.F.; Herrero, M. Re-framing the climate change debate in the livestock sector: Mitigation and adaptation options. *Wiley Interdiscip. Rev. Clim. Chang.* **2016**, *7*, 869–892. [\[CrossRef\]](#)
86. Ali, A.; Erenstein, O. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Clim. Risk Manag.* **2017**, *16*, 183–194. [\[CrossRef\]](#)
87. Greenough, G.; McGeheh, M.; Bernard, S.M.; Trtanj, J.; Riad, J.; Engelberg, D. The potential impacts of climate variability and change on health impacts of extreme weather events in the United States. *Environ. Health Perspect.* **2001**, *109*, 191–198.
88. Vani, D.C.S.; Kumar, D.P.B.P. A Study on Awareness Levels and Adaptation Strategies for Climate Variability among Farmers. *Int. J. Environ. Agric. Biotechnol.* **2016**, *1*, 190–194. [\[CrossRef\]](#)
89. Philip, D.; Rayhan, M.I. *Vulnerability and Poverty: What Are the Causes and How Are They Related?* Term Paper for Interdisciplinary Course, International Doctoral Studies Program at ZEF, Bonn; Universität Bonn: Bonn, Germany, 2004.
90. Wisner, B.; Gaillard, J.C.; Kelman, I. *Handbook of Hazards and Disaster Risk Reduction*; Routledge: London, UK, 2012; ISBN 9780203844236.
91. Jha, S.K.; Mishra, S.; Sinha, B.; Alatalo, J.M.; Pandey, R. Rural development program in tribal region: A protocol for adaptation and addressing climate change vulnerability. *J. Rural Stud.* **2017**, *51*, 151–157. [\[CrossRef\]](#)

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