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Exploring the relationship between information and communication technology (ICT) and productivity: Evidence from Australian farms

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Abstract
The relationship between information and communication technology (ICT) and farm productivity remains unresolved and often debated with limited evidence. While ICT is generally accepted by many to be a positive driver of productivity, others question it. Realistically, truth is likely somewhere in between. Certain ICT investments are likely to facilitate productivity improvement, whereas others may offer some other benefits such as improved safety or reduced emissions. It is also undeniable that some ICT investments may fail or offer little more than a temporary novelty. Using a sample of Australian farm-level data, analysis in this paper finds a positive relationship between ICT investment and productivity. Specifically, the use of precision agriculture and machinery infused with ICT (such as GPS autosteering tractors) is found to be statistically significant. Moreover, digital internet access or access to the National Broadband Network (NBN) is found to be beneficial—and conversely, farms that reported mobile and internet connectivity problems tended to achieve lower productivity.

KEYWORDS
productivity analysis, technology adoption

JEL CLASSIFICATION
Q12, D24, Q16

1 | INTRODUCTION

The productivity benefits of technology to agricultural production are widely researched and generally established (e.g. Coelli, 1996; Mullen, 2007; Nossal & Gooday, 2009; OECD, 1995; Rada & Fuglie, 2019; Sheng et al., 2016). Such studies have analysed the relationship between farm productivity and technology in the context of farm size, input substitution, research and development (R&D) investment, among other factors. Technology and its adoption by farmers have broadly facilitated productivity growth of agricultural industries for many decades. In an Australian context, technology is generally accepted as a driver of productivity (Gray et al., 2014). However, less is known about the nuances of information and communication technology (ICT) investment, particularly in terms of its targeted on-farm use to drive productivity and its barriers to adoption. This study benefits from detailed farm-level ICT data collected under a supplementary survey attached to the annual Australian Agricultural and Grazing Industries Survey (AAGIS). These data have not been previously analysed econometrically and may offer important insights into the relationship between farm-level productivity and ICT investment.

Farm-level decisions to purchase ICT may be influenced by a range of factors. Crop farms, for example, have been previously found to defer some input expenditure due to financial pressure relating to depressed grain prices (Strappazzon et al., 1995). Adoption of innovation has also been observed as important to productivity growth in the case of Australia—with Nossal and Gooday (2009) identifying various avenues by which farmers can take advantage of developments in technology and knowledge. Similarly, input choices and adoption decisions have been previously highlighted as affecting the productivity benefit of technology (OECD, 1995). Farm size is also a factor of ICT adoption, with Strappazzon et al. (1995) explaining that the nature of new technologies has been historically better suited to large-scale farming—hence, large farms have had greater scope for input substitution. The capital base of large farms has extended this advantage, enabling them to invest heavily in expensive technology. Exploring technology access in the context of the farm size to productivity relationship, Sheng and Chancellor (2019) found evidence of this large farm advantage. However, they identified that some small farms may be able to overcome their financial limitations and access similar technology to unlock productivity gains using capital hire.

While technology is broadly accepted to be a driver of farm productivity, the narrower topic of ICT and farm productivity has attracted debate and remains largely unresolved. It is unknown whether all farm ICT investment is beneficial for productivity or whether productivity improvement is always the intention of ICT investment. 'Non-productivity' benefits may be the primary driver of the farm-level ICT investment—for example, to improve safety or comfort. Recent studies have claimed that drones will improve farm productivity (Mogili & Deepak, 2018; Schmeitz, 2020); however, statistical evidence on the topic is limited. Little is known about the complex and integrated human capital effect on ICT investment and its practical implications on using ICT to improve farm productivity.

While not specific to agriculture, Cardona et al. (2013) identified contradictory findings among ICT-productivity studies—yet concluded that the evidence generally indicates a significant positive relationship. Other studies have focussed entirely on the perceived phenomenon that large investment in information technology has yielded marginal productivity gains (Oz, 2005)—otherwise known as the 'IT paradox'. For example, the benefit of ICT on productivity for French dairy farms is questioned by Ghali and Arfa (2017); however, they find that farms equipped with digital tools tend to be more productive than their peers. This aligns with the general consensus of other researchers such that ICT investment is typically positive for farm productivity (e.g. Lio & Liu, 2006; Ogutu et al., 2014; Otter & Theuvsen, 2014). However, explanations for the positive impact of ICT on productivity are mixed. Information and communication technology investment has also been viewed as a facilitator of productivity growth (Dolman, 2009), by improving access to both information and markets, enabling farmers to adjust management behaviour—such as fine-tuning their use of seed and fertiliser inputs. Another observation from the literature is that ICT adoption tends to be higher among richer countries—possibly due to complementary factors such as a higher human capital base (Lio & Liu, 2006). In the case of Australia, several studies have observed or acknowledged ICT investment as positive for agricultural productivity (Connolly & Fox, 2006; Parham, 2002). More specifically, Carberry et al. (2011) found evidence that ICT had assisted Australian dryland farmers to navigate fragile environmental conditions and weather variability. While existing research on the ICT-productivity relationship for Australian agriculture offers valuable insights, the link between productivity and ICT is not definitive due largely to measurement challenges such as data availability and endogeneity (Salim et al., 2016).

The broad objective of this paper is to test the relationship between farm-level total factor productivity (TFP) and farm-level ICT investment. A secondary objective is to observe the relationship between TFP and specific elements of ICT investment (e.g. precision agriculture, drones, and internet access) and ICT impediments (e.g. mobile phone coverage problems). The relationship between farmer age and ICT investment in the context of productivity is explored to identify a potential channel for lifting the productivity of some farms. This study aims at providing new insights for both policymakers and farmers by using a data set not previously used for econometric analysis to explore this important topic. The paper is structured to include a detailed summary of the data and statistics, followed by the method specification, then results are presented and conclusions are discussed.

2 | DATA AND DESCRIPTIVE STATISTICS

This paper benefits from highly detailed farm-level data collected under the AAGIS by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES). The AAGIS sample selection is based on a population derived from the Australian Bureau of Statistics (ABS) and Australian Business Register (ABR). Businesses are included where their estimated value of agricultural operations (EVAO) exceeds $40,000. The full sample of farms in the 2016–2017 AAGIS survey is 1306; however, in total, 71 records were removed due to data errors. The final useable sample was 1235 farms. Note that these ICT statistics were collected for a sample of broadacre, dairy and vegetable farms (see Dufty & Jackson, 2018). However, for this study, the analysis focusses on broadacre farms only, which include cropping, mixed cropping–livestock, sheep, beef and mixed sheep–beef. Dairy and vegetable farms were not included in the econometric analysis due to additional farm-level TFP modelling challenges related to variation in the composition of production inputs and outputs. Nevertheless, the inclusion of these industries may offer important insights and provide a useful avenue for future research, particularly if further ICT data are collected.

2.1 | Data source and summary statistics

For the 2016–2017 financial year, the AAGIS included a supplementary section on ICT. Note that this supplementary section was included only once; therefore, the analysis in this paper is based on a single year of data only. Detailed ICT statistics were collected under this section, including expenditure categories, the use of ICT for record-keeping, operational use including precision agriculture, and ICT accessibility and problems. This special one-off section in the annual AAGIS acknowledged some crossover between the use of ICT assets and services for the farm business and for the farm household. As such, the survey also collected information on ICT used for nonbusiness household purposes (e.g. % of ICT used for nonbusiness entertainment).

Selected descriptive statistics are presented in Table 1 to provide a high-level overview of the data available for analysis. For example, the average age of farm managers tends to be higher than the average age of the person responsible for ICT decision-making on the farm—implying that the farm manager and ICT decision-maker may often be different people. Mobile and digital are the main channels for farm internet access and, no farms in the sample reported using dial-up internet, since this service was ended in 2015 (Sadsuskas, 2015). Large standard deviations for ICT spending (e.g. $7040 for GPS) provide an indication of uneven ICT investment between farms.

Farm productivity, age of farm manager and total ICT expenditure are of particular interest. The limitations of investigating the relationship between farmer age and productivity

TABLE 1 Sample descriptive statistics, 2016–2017 financial year, observations—1235.

Variable	Note	Mean	Std. dev.
Total factor productivity (TFP) (*calculated from the data, not collected directly*)	TFP level	1.730465	0.860776
Age of farm operator	Years	57.60049	11.29132
Age of person responsible for ICT	Years	53.53404	12.06219
Gender of person responsible for ICT	1—male, 2—female	1.405186	0.4911271
Education level of farm manager	(1—no schooling, 2—primary school, 3—1–4 years of high school, 4—5–6 years of high school, 5—trade completed, 6—tertiary completed, 0—not reported)	4.251216	1.332762
Education level of farm manager spouse		4.169368	1.993013
Farm cash receipts	$AUD	$1,565,041	$3,271,288
Nonfarm income	$AUD	$31,481	$78,370
Area operated	Hectares	31,128	161,215
National Broadband Network user	1—No, 2—YES	1.50081	0.5002021
Mobile coverage problems reported	0—No, 1—YES	0.6831442	0.4654393
Social media presence	0—No, 1—YES	0.1004862	0.3007691
ICT used for nonbusiness entertainment	% of total ICT use	23.04%	37.65%
Access fixed wireless	0—No, 1—YES	0.2179903	0.4130481
Access mobile wireless	0—No, 1—YES	0.3047002	0.4604669
Access digital internet	0—No, 1—YES	0.0858995	0.2803292
Access dial-up internet	0—No, 1—YES	0	0
Computer expenditure	$AUD	$343	$1103
Telco equipment expenditure	$AUD	$335	$2463
GPS expenditure	$AUD	$1178	$7040
Devices expenditure	$AUD	$264	$1774
Software expenditure	$AUD	$139	$877
Telco services expenditure	$AUD	$4706	$4602

Source: ABARES.

must be acknowledged, particularly since age does not necessarily reflect skill or experience. Unfortunately, such data are difficult to collect in a meaningful way and unavailable for this study. The analysis to follow makes some effort to control for skill by including a variable for formal education alongside age.

Information in Figure 1 shows a relationship between productivity and farmer age such that productivity appears to peak for farmers in the 31–40 and 41–50 age groups. Similarly, farm ICT spending peaks for the 31–40 age bracket and then steadily declines. Descriptive statistics from the 2016–2017 sample of farms in Figure 1 provide some general support for the 'lifecycle' pattern observed by Tauer (2019). Farmer age, in the context of the 'productivity – ICT relationship', will be explored in further detail throughout this paper.

The analysis to follow will also investigate the observable correlation between farm-level productivity and ICT investment for the sample period, to establish whether a relationship exists given a range of explanatory and control variables.

Farm size variables are defined following the approach used in Dufty and Jackson (2018) such that small farms have receipts of less than $400,000, medium farms have receipts between $400,000 and $1 million and large farms have receipts over $1 million. It is expected that large farms may have increased capacity for ICT investment and increased benefits of adoption (Dufty & Jackson, 2018).

2.2 | Sample and weighting

Although sample weights are available, the analysis will remain unweighted, since the analytical target is to test farm-level variable correlations rather than attempt to derive statistics representative of the entire broadacre population (Winship & Radbill, 1994).

3 | METHOD

Previous studies on the relationship between farm productivity and ICT have used several econometric approaches, dependent on data availability. The Cobb–Douglas production function

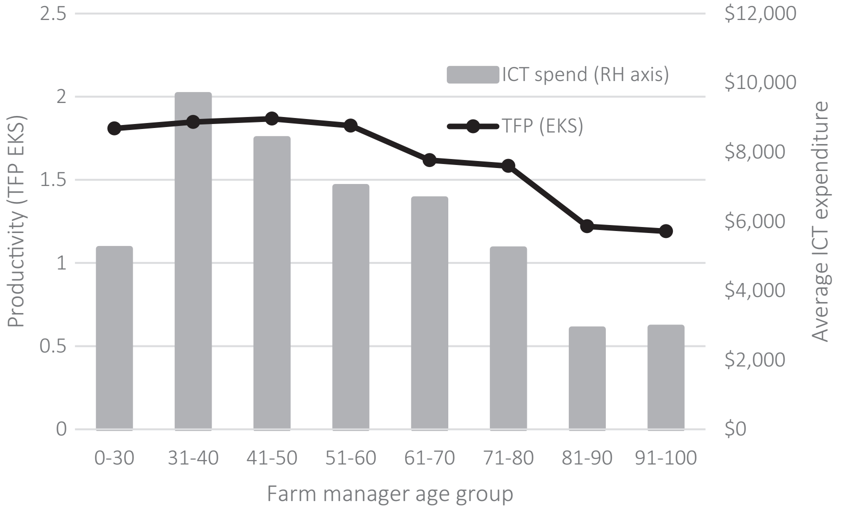

FIGURE 1 Farm-level productivity and ICT expenditure by age group, 2016–2017 sample farms. Source: Authors' estimates

is widely used to generate productivity estimates in such studies (e.g. Cardona et al., 2013; Connolly & Fox, 2006; Lio & Liu, 2006; Salim et al., 2016; Shahiduzzaman et al., 2015). Others have relied on aggregate ABARES TFP broadacre estimates (Khan et al., 2017), following a growth accounting the Fisher index approach.

The dependent variable, farm-level TFP, is generated using the growth accounting the approach developed for the ABARES AAGIS data by Zhao et al. (2012). Price and quantity data for each input and output at the farm level are used to derive farm-specific TFP as a Fisher output index divided by a Fisher input index (as in Sheng et al., 2016; Sheng & Chancellor, 2019). The Fisher index is used due to several attractive properties (including its ability to handle zero values) among other favourable features for the construction of productivity indexes outlined by Fisher (1922), Diewert (1992) and OECD (2001). The Fisher index does suffer from the intransitivity limitation described by O'Donnell (2012), which we address using the Èltetö–Köves–Szulc (EKS) method (Diewert, 1992; Fox, 2003). Total factor productivity is expressed as an index relative to a specific base farm and year such that for any farm-year observation, this measure gives the relative difference in TFP between that and the base observation. For further information, please refer to Zhao et al.'s (2012) study.

A baseline ordinary least squares (OLS) regression model is constructed to test the relationship between productivity and ICT for the sample of 2016–2017 farms (Equation 1).

$$Y_{it} = \beta_0 + \beta_1' X_{it}^A + \beta_2' X_{it}^P + \beta_3' X_{it}^R + \beta_4' X_{it}^E + \beta_5' X_{it}^F + \beta_6' X_{it}^B + \beta_7' X_{it}^C + \epsilon_{it}; \tag{1}$$

$$i = 1, \ \ldots, I; \quad t = 2016 - 17$$

where Y_{it} is the dependent variable and represents farm-level EKS-transformed TFP level for farm i in period$t$. A series of farm-specific vectors are used to explain the dependent variable. X_{it}^A is a vector of ICT access including digital internet and National Broadband Network (NBN) availability; X_{it}^P is a vector of ICT used in farm production including the use of drones and precision agriculture; X_{it}^R is a vector of ICT used for record-keeping and administration; X_{it}^E is a vector to control for nonbusiness and entertainment ICT use; X_{it}^F is a vector of farmer characteristics including age and education; X_{it}^B is a vector of farm business characteristics such as farm size; and X_{it}^C is a control variable vector to account for spatial and farm type variation—specified, respectively, in Appendix Tables S1 and S2. The residual error term is defined as ϵ, and the regression coefficients for each vector are $\beta_1', \beta_2', \ \ldots, \beta_k'$.

Using the same baseline model, the robust regression approach from Hamilton (2012) is applied to calculate variable weights in an effort to control for any outliers and improve the model fit. This approach uses Huber weights (Huber 1964) then biweights (Beaton and Tukey 1974) until convergence to detect influential observations and control for outliers or influential observations. As the sample population is relatively small for the one-off special ICT survey, outliers or influential observations could bias the analysis; therefore, an effort is made to control for this potential bias. The Huber weighting improves the behaviour of the biweight estimator, as demonstrated in Equation 2, where e_r represents the rth residual $Y_r - X_r\beta$ and the median absolute deviation (MAD) from the median residual(med):

$$MAD = med\left(\left| e_r - med\left\{ e_r \right\} \right| \right) \tag{2}$$

where the rth scaled residual u_r is $u_r = e_r / s$, and s is the residual scale estimate. The robust OLS method uses $s = MAD / .6745$ and the Huber estimation finds case weights w_r such that:

$$w_r = \begin{cases} 1 & if\,|u_r| \le c \\ c/|u_r| & otherwise \end{cases} \tag{3}$$

where c is a tuning constant such that$c = 1.345$, meaning that down-weighting begins where absolute residuals exceed approximately $2 \bullet MAD$. The second weighting function used in robust OLS is referred to as 'biweight', where all nonzero residuals receive some down-weighting according to the following function:

$$w_r = \begin{cases} \left[1 - \left(u_r/c\right)^2\right]^2 & if\,|u_r| \le c \\ 0 & otherwise \end{cases} \tag{4}$$

Large residuals $\left(|u_r| \ge c\right)$ result in zero weights and severe outliers are dropped. The biweight iterations employ a tuning constant of $c = 4.685$, meaning that cases with absolute residuals of $7 \bullet MAD$ or more are assigned zero weights (and dropped). The tuning constants $c = 1.345$ (*Huber*) and $c = 4.685$ (*biweight*) give these robust procedures about 95% of the efficiency of OLS when applied to data with normal distributed errors.

The regression analysis is further extended using a between-effects estimator, to test the effect of differences in explanatory variables between farms in the single period. While offering limited additional analytical insight or evidence, this model serves as a form of robustness of the baseline model. Between effects takes the mean of each variable as in Equation 5:

$$\overline{Y}_i = \beta_0 + \beta_1'\overline{X}_i^A + \beta_2'\overline{X}_i^P + \beta_3'\overline{X}_i^R + \beta_4'\overline{X}_i^E + \beta_5'\overline{X}_i^F + \beta_6'\overline{X}_i^B + \beta_7'\overline{X}_i^C + \overline{\epsilon}_i; \tag{5}$$

To improve the between-effects estimator, the data set is resampled 100 times using bootstrapping (Stata, 2014). This process builds a data set of replicated statistics and calculates standard error using the standard formula for the sample standard deviation:

$$\widehat{se} = \left\{ \frac{1}{\sigma - 1} \sum \left(\widehat{\theta}_{be} - \overline{\theta} \right)^2 \right\}^{1/2} \tag{6}$$

where $\widehat{\theta}_{be}$ is the statistic calculated using the $be'th$ bootstrap sample, σ is the number of replications and $\overline{\theta}$ is the average of bootstrapped estimates.

3.1 | Productivity and age

The downward Lowess trend in Figure 2 implies that productivity (of our sample) declines with age; conversely, the upward trend in Figure 3 implies that farms that spend more on ICT have higher productivity levels. This simple correlation provides an indication that a positive relationship between TFP and ICT expenditure for the sample of farms exists. However, this correlation is limited by the endogeneity problem arising by using a Lowess smoother to observe the relationship between two variables only. The next step of the analysis will therefore incorporate a comprehensive range of variables to control for the various factors that contribute to farm-level TFP in addition to ICT investment.

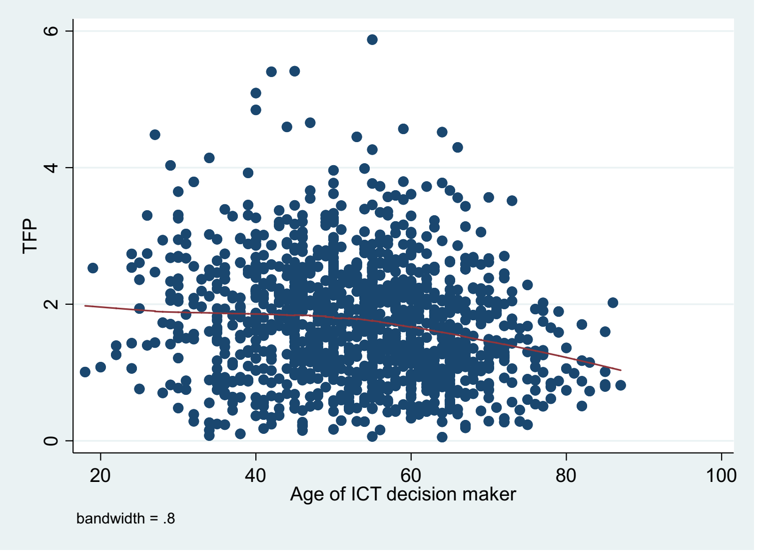

FIGURE 2 TFP and age of ICT decision-maker. Source: Authors' estimates. [Colour figure can be viewed at wileyonlinelibrary.com]

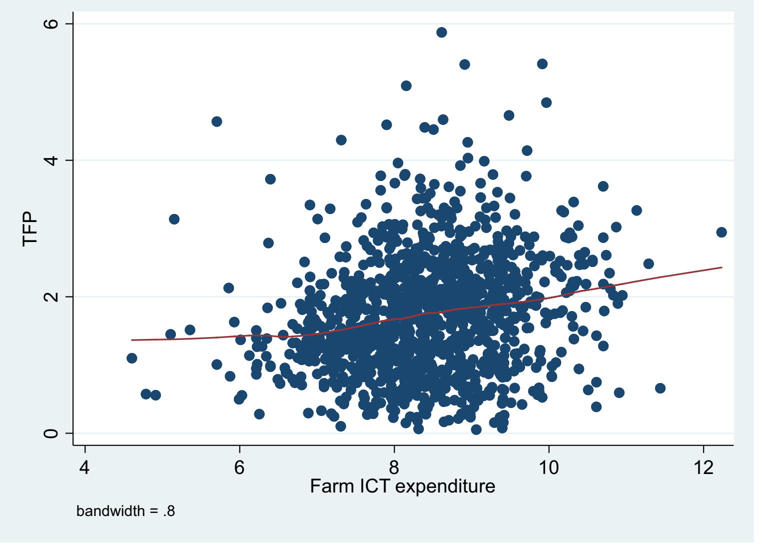

FIGURE 3 TFP and farm ICT expenditure. Source: Authors' estimates [Colour figure can be viewed at wileyonlinelibrary.com]

4 | EMPIRICAL RESULTS

Beginning with a baseline OLS model, the relationship between productivity and ICT expenditure is examined within the context of covariates and control variables. Extending the OLS model, robust regression and between-effects estimators are also used. These models control for the extensive farm-level ICT attributes, characteristics of the farmer and farm, as well as for farm type, size and location. Rather than implicitly testing the relationship between total ICT expenditure and productivity in the base model, the availability of detailed ICT variables

TABLE 2 Relationship between TFP and ICT for a sample of Australian broadacre farms

Variables	Variable description	Ordinary least squares	Robust regression	Between-effects regression with bootstrap
Dependent variable: TFP	EKS-transformed farm-level total factor productivity			
ACCESS	Inadequate mobile access	−0.0831	−0.0922*	−0.0833
		(0.0509)	(0.0478)	(0.0532)
	Inadequate internet access	−0.0679	−0.0830**	−0.0686
		(0.0445)	(0.0418)	(0.0483)
	Mobile coverage problems	−0.185***	−0.161***	−0.185***
		(0.0483)	(0.0453)	(0.0546)
	Digital internet access at farm (e.g. ADSL)	0.193***	0.151**	0.195**
		(0.0679)	(0.0638)	(0.0788)
	Fixed wireless access at farm (e.g. Wi-Fi)	0.0956**	0.0890**	0.0970**
		(0.0453)	(0.0425)	(0.0490)
	National Broadband Network (NBN) access at farm	0.0947**	0.0958**	0.0933**
		(0.0399)	(0.0374)	(0.0365)
PRODUCTION	ICT used to operate farm machinery (e.g. GPS guidance)	0.00216***	0.00193***	0.00213***
		(0.000716)	(0.000672)	(0.000748)
	Precision agriculture tools used	0.220***	0.242***	0.223***
		(0.0568)	(0.0534)	(0.0510)
	Drones used	0.124	0.106	0.125
		(0.0871)	(0.0818)	(0.0953)
RECORDS	ICT used for agricultural news	0.0792*	0.0782**	0.0785**
		(0.0404)	(0.0379)	(0.0391)
	Farm business web presence	−0.0254	−0.0375	−0.0252
		(0.0734)	(0.0690)	(0.0760)
	ICT used for record-keeping	−0.0725	−0.1000*	−0.0730
		(0.0589)	(0.0553)	(0.0555)
	Farm business social media presence	−0.276***	−0.228***	−0.276***
		(0.0738)	(0.0693)	(0.0718)
ENTERTAINMENT	ICT used for nonbusiness activities	−0.220***	−0.252***	−0.221***
		(0.0459)	(0.0431)	(0.0491)
	ICT used for children's education	−0.00419***	−0.00417***	−0.00418***
		(0.000991)	(0.000931)	(0.000896)
	ICT used for other nonbusiness activities	−0.00220***	−0.00265***	−0.00220***
		(0.000634)	(0.000596)	(0.000607)

(Continues)

TABLE 2 (Continued)

Variables	Variable description	Ordinary least squares	Robust regression	Between-effects regression with bootstrap
FARMER	Age of farm business manager squared	−2.48e-05	−1.76e-05	−2.47e-05
		(2.03e-05)	(1.90e-05)	(2.29e-05)
	Education level of farm business manager spouse	0.00980	0.0182*	0.00953
		(0.0104)	(0.00974)	(0.0107)
	Education level of farm business manager	0.0507***	0.0490***	0.0506***
		(0.0157)	(0.0147)	(0.0131)
	Age of person primarily responsible for ICT on the farm squared	−1.98e-05	−1.59e-05	−1.97e-05
		(2.07e-05)	(1.94e-05)	(2.43e-05)
	Gender of person primarily responsible for ICT on the farm	−0.0883**	−0.0812**	−0.0884**
		(0.0378)	(0.0355)	(0.0419)
BUSINESS	Family farm flag	0.0356	0.0307	0.0364
		(0.0733)	(0.0688)	(0.0738)
	Small farm size	-	-	
	Medium farm size	0.257***	0.250***	−0.276***
		(0.0517)	(0.0486)	(0.0538)
	Large farm size	0.535***	0.484***	
		(0.0512)	(0.0481)	
CONTROL	Region identifier to control for spatial variation	−0.000592***	−0.000641***	−0.000587***
		(0.000115)	(0.000108)	(0.000126)
	Farm type control variable	−0.173***	−0.168***	−0.172***
		(0.0179)	(0.0168)	(0.0180)
Constant		2.395***	2.371***	2.929***
		(0.183)	(0.172)	(0.196)
Observations		1235	1235	1235
R-squared		0.478	0.496	0.477

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard deviations in brackets.

allows for additional analysis of ICT covariates. In other words, the variables that make up ICT investment are separately observed as independent variables alongside various control variables. This allows for a detailed analysis to test the specific components of ICT investment in relation to farm productivity (Table 2).

To test the relationship between ICT and farm productivity in detail, the individual variables are listed in Table 2 grouped by types of ICT characteristics. Beginning with the 'ACCESS' vector, mobile and internet access problems are found to be negatively related to TFP—implying that farms exposed to mobile coverage problems, for example, exhibited a TFP level lower by 0.083 for the sample of 2016–2017 farms. For context, the mean productivity level for the sample farms in this period was 1.73; therefore, farms with mobile coverage problems tend to have productivity levels approximately 4.80% lower than average farms. By contrast, access to digital internet, fixed wireless and the NBN were all found to be significant and positively correlated with TFP—implying that farms with access to these services obtain a productivity benefit of 0.193, 0.095 and 0.095, respectively, in the base OLS model.

For the 'PRODUCTION' covariates, ICT machinery and precision agriculture are all found to be significant and positively correlated with TFP. The use of precision agriculture was found to have a largely positive relationship with productivity of 0.220. A significant relationship between unmanned aerial vehicle (UAV) (*drone*) investment and farm TFP was not identified in this period.

Not all ICT covariates appear to be important or beneficial for farm productivity. Those in the *RECORDS* group such as using ICT for record-keeping or a farm business web presence were not significant. Information and communication technology used for agricultural news and research was positive and significant in all models, which appears to be reasonably intuitive. An internet-enabled computer can offer fast access to very detailed and timely information (e.g. weather reports, crop variety research and price trends) compared with traditional methods of news and research (e.g. newspapers and hardcopy publications). A negative and significant relationship between farm business social media presence and farm productivity was identified in all models. This finding aligns with other studies that have highlighted the potentially distracting nature of social media (Brooks, 2015); yet, others argue the benefits of social media to productivity and agricultural trade (Fafchamps & Minten, 2002). This finding presents an avenue for future analysis once additional farm ICT data are available.

Following the farm business social media presence variable, the *ENTERTAINMENT* group of covariates was included in the analysis due to the crossover between the use of ICT assets and services for the farm business and for the farm household. It was thought that there may be indirect farm business productivity benefits associated with these variables—for example, access to ICT for nonbusiness activities may enable the farm manager to purchase groceries and other personal items online, thereby freeing up additional time to concentrate on farm management. However, the findings contradict this and indicate a negative and significant relationship between farm productivity and these ICT entertainment variables, further supporting the 'distraction' argument in Brooks (2015).

The remaining groups, *FARMER* and *BUSINESS*, assist with endogeneity control, capturing important productivity drivers including age and education. These variables yield expected findings such that education is typically beneficial for productivity (i.e. Tauer, 1984; Triplett, 1999); however, age is not found to be significant in its quadratic form. Age was expected to follow a lifecycle relationship with productivity—increasing to some peak of optimal skill, experience and physical capacity, and then gradually declining (Tauer & Lordkipanidze, 2000). The farm size variables indicate that larger farms experience a greater productivity benefit from ICT investment, aligning with expectations and past research (e.g. Sheng & Chancellor, 2019).

Overall, the evidence suggests that ICT is beneficial for farm productivity—particularly when used to improve the production process through precision agriculture and other technological advancements. However, there is some evidence that components of ICT are negatively correlated with farm productivity as they possibly distract some labour input away from productive farming activity—however, it may also be the case that such ICT use has other long-term benefits such as to well-being, safety or access to training.

4.1 | ICT investment and TFP level in the context of farmer age

In the previous section, the relationship between ICT and productivity was tested for the sample of 2016–2017 farms. Although age was not found to be significant in its non-linear form, consideration was given to whether the high average age of farmers (57.6 for this sample) may present a barrier to ICT adoption for some (e.g. Mitzner et al., 2019). The data set facilitates the analysis of farmer age and ICT, by including two separate age variables—'farm manager age' and the 'age of the ICT decision maker'. In other words, the ICT decision-maker could be

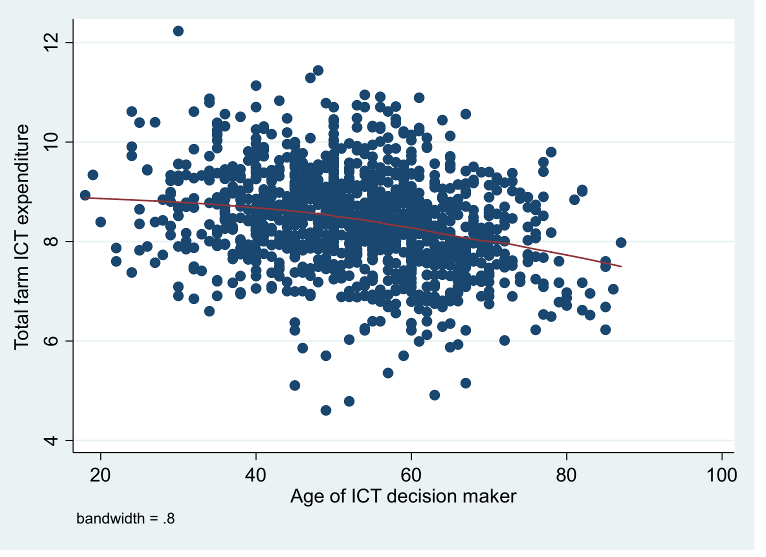

FIGURE 4 Lowess of ICT spending and age. Source: Authors' estimates [Colour figure can be viewed at wileyonlinelibrary.com]

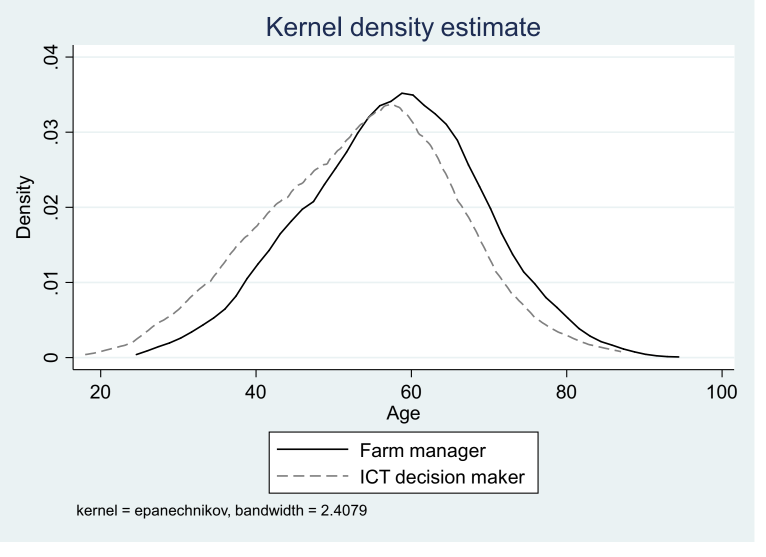

FIGURE 5 Kernel density of farmer age. Source: Authors' estimates [Colour figure can be viewed at wileyonlinelibrary.com]

the farm manager, the farm manager's child, partner, friend, contractor, etc. who they might delegate ICT investment decisions. A Lowess smoother is used to test this relationship between the age of the ICT decision-maker on the farm and the log of farm ICT spending. Figure 4 confirms that for the 2016–2017 sample of farms—ICT spending is highest among younger farmers and tends to decline with age.

The statistical distribution in Figure 5 indicates that the age of the person primarily responsible for the ICT in the farm business tends to be younger than that of the farm manager. Additional testing (*not presented*) confirms that this trend holds across the different

TABLE 3 Robustness checks.

	Ordinary least squares (baseline model)	Interpretation
Breusch–Pagan / Cook–Weisberg tests for heteroscedasticity	chi2(1) = 40.97 Prob > chi2 = 0.0000	Fail—possible heteroscedasticity in the model
White's test for Ho: homoskedasticity against Ha: unrestricted heteroscedasticity	chi2(358) = 408.31 Prob > chi2 = 0.0341	Fail (borderline) —possible heteroscedasticity in the model
Ramsey RESET test—omitted variables	F(3, 1204) = 1.24 Prob > F = 0.2921	Passed—no omitted variable bias
Model specification test, missing variables	_hatsq = P > |t| 0.100	Passed—model correctly specified
Multicollinearity	Mean VIF = 1.54	Passed—no multicollinearity

Source: Authors estimates.

farm types (e.g. cropping, mixed, beef and sheep). It implies that many farm managers may delegate ICT spending decisions to younger family members or employees. If it is possible to assume that younger farmers are inherently more skilled on average in the practical use of ICT to improve productivity, the link between human capital (in the context of ICT skills) and ICT investment may present an avenue for future research in the context of farmer age and farm productivity. However, detailed time series data on formal and informal ICT skill are required to firmly test this hypothesis. Since the results in this paper generally find a positive ICT–TFP relationship, some farmers underinvesting in ICT may be forgoing potential gains in productivity. This productivity barrier could potentially be overcome through introductory training and support, assisting some farmers to adopt productivity-enhancing ICT.

5 | CONCLUSION

Aligning with previous research and intuition, this study finds a positive relationship between farm productivity and ICT investment. The use of ICT in the farming production process, the importance of ICT access and the farm size disparity stand out from the results. These findings may be useful in policy discussion, such as in efforts to lift farm productivity generally or to lift the performance of small farms through technology uptake. If the lack of basic ICT access is an impediment to farm productivity, then this may also provide useful insights for policymakers interested in ICT infrastructure. More broadly, the findings in this paper offer some encouragement that public and private sector investments into ICT research and development have materialised into enhanced productivity for farms that have adopted ICT.

This study offers new insights from a data set not previously analysed econometrically alongside productivity. However, it does suffer from several limitations, mainly related to data. While the data set is highly detailed and at farm level, it is only available for one financial year. Therefore, it is not currently possible to observe the impact of ICT investment on farm TFP over time. These data are also relatively dated now (2016–2017) on a topic that is evolving quickly. As such, there is a strong case to collect ICT data again in future for the purposes of up-to-date time series analysis. Future farm-level ICT data collections could facilitate analysis and build evidence in this important field of research.

5.1 | Robustness checks

To test the validity of the results, postestimation regression diagnostics are calculated for the baseline model. First, the regression specification error is tested for omitted variables (Ramsey, 1969 in Torres-Reyna, 2007). The omitted variable bias test uses the assumption that the error term and the independent variables are not correlated. Second, model specification error is tested using the specification link test proposed by Tukey (1949) and described in StataCorp (2005). Third, a multicollinearity test verifies the assumption that the independent variables are not linear functions of each other. This test generates a variance inflation factor (VIF) for each explanatory variable (Stata, 2015), which is then observed within the context of an acceptable VIF range. Fourth, the Breusch and Pagan (1979) and Cook and Weisberg (1983) tests for heteroscedasticity are used to test whether residuals are homogeneous (Stock & Watson, 2008; Torres-Reyna, 2007). White's test for unrestricted forms of heteroscedasticity is also used (White, 1980).

The heteroscedasticity test is based on the null hypothesis that the variance is homoscedastic, meaning the variance for each observation is relatively similar. The test results in

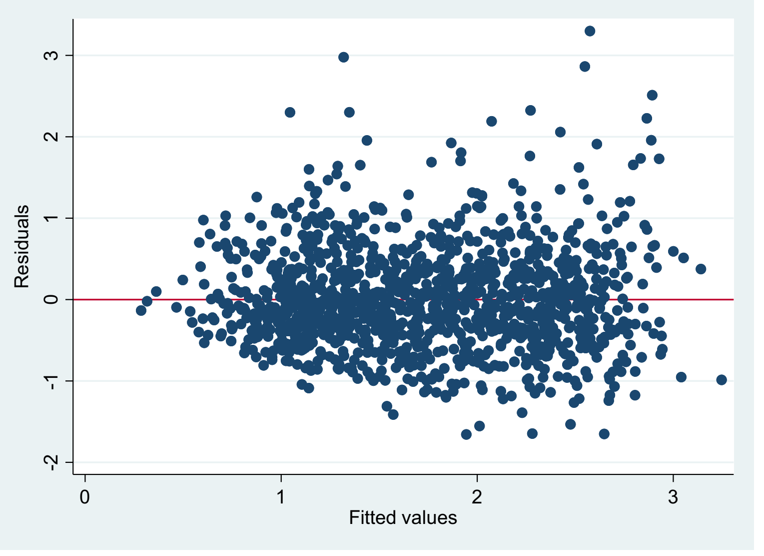

FIGURE 6 Residual versus fitted values. Source: Authors' estimates [Colour figure can be viewed at wileyonlinelibrary.com]

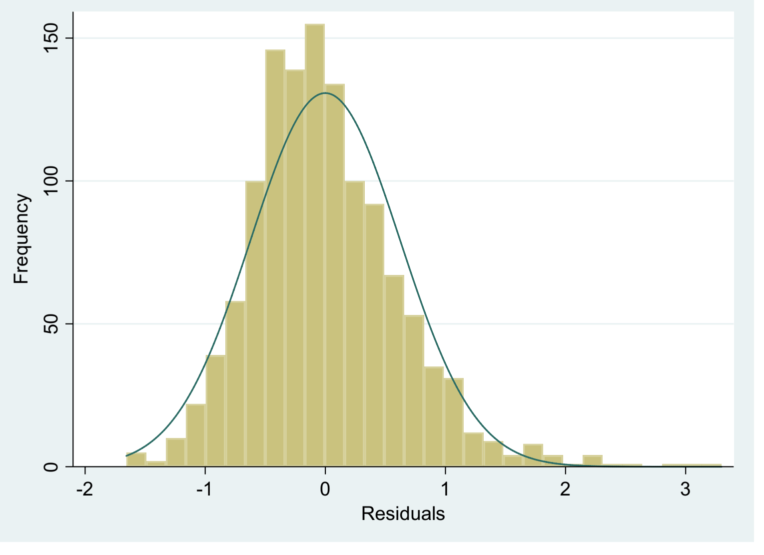

FIGURE 7 Residual, frequency and skewness. Source: Authors' estimates [Colour figure can be viewed at wileyonlinelibrary.com]

Table 3 indicate the presence of heteroscedasticity. This issue is investigated further in Figure 6, which indicates some slight trend towards higher residuals. The degree of heteroscedasticity appears to be minor with most points relatively evenly distributed along the Y-axis.

An additional test (White's test) indicates the borderline presence of heteroscedasticity (Table 3), prompting further investigation. Residuals are predicted and plotted in Figure 7, revealing some very minor skewness towards the left. These investigations confirm that the presence of heteroscedasticity is relatively minor and that the regression results therefore remain sufficiently robust and valid. As an additional validation, the baseline regression was rerun using a variance estimator robust to heteroscedasticity (Huber/White/sandwich estimator). A comparison of this model output with that of the original baseline model concluded no major differences.

For the omitted variables test, the null hypothesis is that the model does not have omitted variable bias (i.e. a *p*-value exceeding 95%). Since the *p*-value exceeds 0.05 (0.2921), the model fails to reject the null hypothesis and concludes that the model does not suffer from omitted variable bias. The model specification test performs a regression of TFP on its predicted and predicted squared version such that if the model is specified correctly then the prediction-squared should have no explanatory power. The prediction-squared exceeds 0.05 (0.100) and therefore passes the specification error test. The test of multicollinearity is based on a VIF such that a mean VIF of greater than 10 indicates the possible presence of multicollinearity (Torres-Reyna, 2007). The mean VIF value in Table 3 is less than 10 (1.54) and confirms that the model does not suffer from multicollinearity.

DATA AVAILABILITY STATEMENT

Due to the confidential unit record data used for this study, summary statistics are available only.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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