Impacts of interlocked contractual arrangements on dairy farmers’ welfare in Zambia: a robust Bayesian instrumental variable analysis

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ABSTRACT

While contract farming and interlocked contractual arrangements (ICAs) are generally perceived to resolve persistent market failures and improve smallholder farmers' welfare in developing countries, uncertainties remain as to whether these arrangements enhance welfare because of farmers' low marketed volumes and margins. To account for potential selection bias, non-Gaussian and missing data problems, a robust two-stage Bayesian instrumental variable approach is used to determine the impact of dairy farmers' participation in ICAs on household income and milk revenue. Data are from smallholder dairy farmers in Zambia. We find that male household heads, wealth, experience selling to milk collection centres (MCCs), livestock holding, milking parlour ownership, landholding, and access to marketing information positively affect farmers' probability to participate in ICAs. However, increased off-farm income and distance to MCCs limit their participation. While some socioeconomic variables have significant positive effects of affecting ICA participation on household welfare, we find no sufficient evidence of causal effects of ICAs on household incomes and milk revenue among dairy farmers. Thus, while ICAs enhance smallholder farmers' access to markets, they may not address high rural poverty rates in developing countries. We provide some insights by which performance of ICAs in the dairy sector may be improved.

KEYWORDS: Agricultural value chains, Bayesian analysis, contract farming, instrumental variables, Zambia

1. Introduction

Recently, there has been increasing interest in all types of contract farming arrangements for smallholder farmers in developing countries because of the rising concern that smallholder farmers are excluded from mainstream value chains (Fitawek et al. 2020; Olounlade et al. 2020; Bellemare and Novak 2017; Bellemare 2012; Fréguin-Gresh and Anseeuw 2013; Maertens and Swinnen 2009; Miyata, Minot, and Hu 2009; Reardon et al. 2009). However, uncertainties persist about whether smallholder farmers truly benefit from participating in interlocked contractual arrangements (ICAs) and mainstream value chains such as those in the crop sector. Fréguin-Gresh and Anseeuw (2013) find that contract farming is limited and mostly benefits the already better-off farmers. Fréguin-Gresh and Anseeuw (2013) further suggest that contract farming does not provide an efficient means of reducing poverty, nor an institutional tool to improve rural livelihoods in South Africa. Moreover, Olounlade et al. (2020) find significant negative effects of contract farming among rice farmers in Benin whereby contract farming significantly reduces production income and food consumption among rice farmers. Fitawek et al. (2020) find that contracted farm households in Madagascar are generally more food insecure than otherwise.

On the contrary, Miyata, Minot, and Hu (2009) suggest that contract farming can help raise farm income among apple and green onion farmers in China while Bellemare (2012) finds that a 1% rise in the probability of participating in contract farming is associated with a 0.5% rise in household income among crop farmers in Madagascar. Bellemare and Novak (2017) find that contract farming makes participating households to be about 18% more likely to have their hungry season end at any time. These mixed results do not strike down the common perception that other value chain participants, such as middlemen, traders and processors, reap a greater share of returns, while smallholders are exploited (Sivramkrishna and Jyotishi 2008; Bellemare 2012;

Fréguin-Gresh, D'Haese, and Anseeuw 2012). Meanwhile, whereas the absolute number of smallholder farmers participating in mainstream value chains through contract farming is high, their marketed volumes and margins are low (Anseeuw, Fréguin-Gresh, and Davis 2016; Fréguin-Gresh and Anseeuw 2013; Helin, Lundy, and Meijer 2009; Minten, Randrianarison, and Swinnen 2009).

Nonetheless, contract farming is perceived by many as one of the approaches to resolve persistent agricultural market failures for smallholder farmers (Da Silva and Rankin 2013; Han, Trienekens, and Xu 2013; Jia and Bijman 2013). This is particularly true in the context of market liberalisation, globalisation, reduced government-farmer support, changing consumer preferences, and procurement systems. ICAs are a form of contract farming, where contractors not only provide a market outlet for farmers' produce. ICAs also provide resources or link farmers to providers of key inputs, extension and financial services, of which the costs of doing so are usually deducted from proceeds at the point of sale. These institutional arrangements reduce information asymmetry, production and market risks (Setboonsarng, Leung, and Stefan 2008), and guarantee product quality and food safety standards (Prowse 2012). Consequently, smallholder farmers' household income is likely to increase because of repeat business, consistency in product sales and income, improved productivity and product quality, receiving a premium price for delivering a quality product, and enhanced diversified livelihoods.

In Zambia – a Southern African country, the private sector (i.e., agro-product processors, input, financial and other service providers), with non-governmental organisations (NGOs) and the government, have formed productive commercial relations with smallholder dairy farmers as suppliers and customers. The Zambian government, in collaboration with NGOs, such as Land O'Lakes, Heifer Project International, Agricultural Support Programme, MUSIKA Zambia Ltd, Zambia Agribusiness Technical Assistance Centre, the Herd Book Society of Zambia and World Vision, have facilitated smallholder farmers' linkages to the modern dairy value chain (Kiwanuka and Machethe 2016). These institutions have achieved this by organising dairy farmers into producer cooperatives, providing them with improved breeding animals, technologies and extension services, and building milk collection centres (MCCs) equipped with milk cooling and testing facilities (CAPRA 2013). The subsequent organisation of producers and establishment of MCCs has encouraged processors (e.g., Parmalat Zambia Ltd, Zambeef, Nice Product and Varun Food and Beverages), input providers (e.g., feed, milking equipment, veterinary services), formal financial institutions (e.g., Zambia National Commercial Bank and Micro Bankers Trust) and insurance companies to partner with smallholder dairy farmers. In doing so, smallholder farmers are provided with the necessary inputs and services through ICAs. Thus contemporary ICAs represent a more holistic and sustainable approach to rural development.

While contract farming is generally associated with improved welfare (Bellemare 2012; Barrett et al. 2012) and increased efficiency (Mishra, Rezitis, and Tsionas 2019), the impact of the dairy sector's ICAs on household welfare in developing countries has received limited attention. Most peer-reviewed empirical studies on contract farming have rather focused on the crop sector (e.g., Manda, Tallontire, and Dougill 2020; Mugwagwa, Bijman, and Trienekens 2020; Masasi and Ng'ombe 2019; Sokchea and Culas 2015; Sambuo 2014; Cahyadi and Waibel 2013; Escobal and Cavero 2012; Fréguin-Gresh, D'Haese, and Anseeuw 2012; Michelson, Perez, and Reardon 2012; Bellemare 2012; Jones and Gibbon 2011; Vermeulen, Kirsten, and Sartorius 2010; Bolwig, Gibbon, and Jones 2009; Saigenji and Zeller 2009; Chamberlain and Anseeuw 2017; Maertens and Swinnen 2009; Miyata, Minot, and Hu 2009; Minten, Randrianarison, and Swinnen 2009; Ramaswami et al. 2006). Only a handful of peer-reviewed journal articles have directly analysed the impacts of contract dairy farming on farmer welfare. These include Bernard et al. (2018), Kiwanuka and Machethe (2016), Saenger et al. (2013), Noev, Dries, and Swinnen (2009), and Birthal, Joshi, and Gulati (2005). Bernard et al. (2018) investigate the impacts of including a nutrition-based incentive in contracts between a dairy processing factory and its semi-nomadic milk suppliers in Senegal. Kiwanuka and Machethe (2016) examine the determinants of smallholder farmers' participation in Zambia's dairy markets through ICAs. Saenger et al. (2013) use framed field experiments among Vietnamese dairy farmers to better understand relationships among contractual pricing schemes, output quality, and input use. Noev, Dries, and Swinnen (2009) investigate the main developments in the Bulgarian dairy sector while Birthal, Joshi, and Gulati (2005) examine how smallholder farmers including those in the dairy sector could benefit from the emerging opportunities in high-value Indian agriculture.

Given the relatively sparse literature on this dimension of impacts of contract dairy farming on the welfare of participating households, the jury is still out on whether ICAs improve welfare. Our intuition suggests ICAs in the dairy sector should, at a minimum, increase expected household welfare of farm households involved. Otherwise, based on random utility maximisation theory, dairy farmers would rationally choose not to participate in ICAs but rather in other alternatives. Nevertheless, participation in contract farming is typically influenced by unobserved factors (e.g., farmer intelligence, innate abilities, motivation, industriousness, and risk perception among others) that may be correlated with participation and welfare outcomes and thus bias results (Miyata, Minot, and Hu 2009; Bellemare 2012). Additionally, the fact that there is scanty peer-reviewed empirical literature that examines the impacts of dairy sector ICAs on household welfare, makes causal statements about ICAs on dairy farmers' welfare seemingly elusive. Motivated by these concerns, this study analyses determinants of dairy farmers' participation in ICAs and the impacts of dairy sector ICAs on household welfare. Specifically, first, we empirically examine factors that affect dairy farmers' participation in ICAs, and then, determine the impact of participation in ICAs on milk revenue among smallholder dairy farmers in Zambia. Third, we determine the impact of smallholder dairy farmers' participation in ICAs on household incomes in Zambia.

Our paper's contribution to the existing literature on the impacts of contract farming is twofold. First, while there is a growing body of research, modelling the impacts of contract farming arrangements on household welfare, as pointed out before, a dearth of empirical research that directly analyses their impacts in the dairy sector still exists. Yet, the dairy sector is an important component of agriculture, and with vast potential to improve smallholder farm households' welfare (Douphrate et al. 2013; Ulicky et al. 2013). In this sense, this paper seeks to make a more general empirical statement about the causal effects of ICAs by extending the analysis to the dairy sector.

Most importantly, the second contribution lies in the way the paper identifies the causal effects of ICAs on household incomes and milk revenue. As pointed out by Bellemare (2012), people's participation in contract farming is not randomly distributed across farm households. Agricultural producers in the dairy sector may self-select themselves into such contracts based on unobservable confounders such as farmer intelligence, innate abilities, motivation, industriousness, and risk perception among others that may affect both participation and the outcome of interest. To correctly and econometrically identify the causal effects of participation, one needs to identify a suitable instrumental variable (IV). This implies that a researcher would have to identify a variable that acts as a natural experiment on participation – a variable that would affect participation in ICAs but plausibly exogenous to the outcome of interest. Such a variable would block correctly the potential bias from confounders. It is worth noting that using ordinary least squares (OLS) does not solve the problem because OLS only accounts for observable factors such as age, household size, off-farm income and others. The IV's magic is that it makes the whole analysis work like the sample was from a random experiment. This is plausible because if a farmer's intelligence or industriousness (which are unobservable) help her to participate in ICAs, it is also possible that the same intelligence or industriousness can help her do other tasks that bring her revenue or buy milk from other farmers and sell it in ICAs. This means that because of intelligence/industriousness that are unobservable, the farmer can have more household income or milk revenue that may not be due to her participation in ICAs. Thus, attributing all the household income or milk revenue to participation in ICAs would be inappropriate because intelligence/industriousness were not accounted for since these are unobservable. Without finding a suitable IV, one's causal effects of ICAs would therefore be biased and inconsistent (Wooldridge 2002; McElreath 2020). In other words, with a suitable IV, the effect of intelligence and other unobservables is blocked in the analysis, as demonstrated in the next sections.

To provide reliable and consistent estimates, this paper uses a robust two-stage Bayesian instrumental variable approach to account for potential selection bias of participation in ICAs and non-Gaussian and/or missing data prevalent in observational studies. The Bayesian methods used in this paper are cutting edge and automatically handle ignorable missing and non-Gaussian distributed outcome data (Shi and Tong 2016, 2017, 2020). Besides, Bayesian estimation is conceptually appealing as its inference is exact and valid for any sample size (Gelman et al. 2013; Shi and Tong 2016, 2017; Ng'ombe and Boyer 2019; McElreath 2020; Shi and Tong 2020). To the best of our knowledge, this article represents a first step towards applying robust two-stage Bayesian IV techniques in agricultural and applied economics.

The rest of the paper is organised as follows. The next section describes the data used. Then we present modelling and estimation strategies in section 3 followed by empirical results in section 4. Section 5 presents the conclusion and policy implications.

2. Data

2.1 Data sources

This study was carried out in two milk shed areas of Lusaka and Central provinces of Zambia. Milk sheds are areas of high concentration of milk production mostly for the commercial markets in Zambia. Within the selected milk shed areas the study concentrated on three districts, Chibombo and Kabwe districts in Central province and Chongwe district in Lusaka province.

A cross-sectional household survey of smallholder dairy farmers owning one to fifty animals was conducted in 2015. A multi-stage sampling design was used for the study. First, the two milk shed areas, were purposively selected based on (i) the presence and activity of ICAs and; (ii) their proximity and accessibility to us. Second, purposive sampling was used to select four MCCs in the two districts, representing 9.3% of the 43 MCCs existing in Zambia. Third, a two-stage cluster sampling design was used to randomly select the primary sampling units or standard enumeration areas in the first stage and the secondary sampling units in the second stage. In the first stage sampling frame, all standard enumeration areas within a radius of 20 kilometres from each of the four selected MCCs were included.

The study's sample size was determined using the sample size calculation formula and various assumptions were used to compute it. These included estimation of the expected mean and standard deviation of household income for the control and treatment groups of the proposed study based on statistics from a CAPRA (2013) household survey of dairy farmers in Zambia; statistical power, significance level and estimated response rate of 0.86, 0.05 and 90% respectively. Also, a ratio of 3:2 of the sample size of the control group to treatment group was used in to take care of selection biases, since selection of participants in ICAs was not done randomly. The estimated optimal sample sizes came to 171 and 113 for the control and treatment groups, respectively. However, due to non-response, the final sample size came to 105 and 98 for the control and treatment groups, respectively, resulting in a total of 203 households.

Meanwhile, the three firms were purposively selected since there were the off-takers/buyers for the sampled MCCs. In this study, for privacy reasons, we hypothetically refer to the three selected firms as Firms A, B, and C. Firms A and B are vertically integrated, controlling the various value chain stages, from production to processing through the milk distribution. Moreover, Firm A is a public limited company producing 52.25% of the milk it processes, while Firm C is owned by dairy cooperative members. In contrast, Firm B was a private limited company that outsourced all the milk it processed from local dairy farmers. Farmers signed agreements with an off-taker/buyer in their area through their MCCs. Despite contracts being from the three different companies with their own requirements, they operated based on the main tenets of ICAs whereby farmers were required to deliver high-quality milk to buyers they signed contracts for. Due to limited space, comprehensive descriptions and comparisons of the nature of the agreements, contract terms, farmers' payment date, milk price, acceptable milk grade, and the type of inputs and services offered under the ICAs are shown in Supplementary Table A1 in the Appendix.

Table 1 shows a description of the variables that we used in this study. Column 1 of Table 1 shows variable names while column 2 presents descriptions of the variables.

Table 1. Definitions of variables used in the analysis.

Variable name	Variable description
Treatment variable	
Interlocked contractual arrangements (ICAs) participation	Farm household participates in ICAs, equals 1, if yes, 0 otherwise
Outcome variables	
Log of household income	Log of the reported household income previous 12 months
Log of milk revenue	Log of milk revenue realised in previous 12 months.
Explanatory variables	
Age (years)	Age of household head in years
Gender	Gender of household head, equals 1, if male, 0 otherwise
Marital status	Marital status of household head, equals 1 if married, 0 otherwise
Household size	Total number of members in the household
Education	Years of education of the household head
Dairy skills	Household head is skilled in dairy production, equals 1 if yes, 0 otherwise
Log of other income	Log of off-farm income
Wealth index	Standardized wealth index for each household
Experience selling to milk collection centres (MCC)	Years of experience of selling milk to MCCs
Access to dairy information	Access to dairy marketing information, equals 1 if yes, 0 otherwise
Duration in farmer cooperation	Total number of years household head belonged to farmer cooperative
Livestock holding (total livestock units (TLU))	Amount of livestock a farmer has measured in TLU
Distance to MCC (km)	Distance from farm household to milk collection centre in km
Distance to milk trader (km)	Distance from farm household's farm to milk trader in km
Proportion of milk sold (%)	Proportion of milk (out of the total produced) that is sold through ICAs.
River	Source of water for dairy animals is a river, equals 1 if yes, 0 otherwise
Dams-lake	Source of water for dairy animals is a dam lake, equals 1 if yes, 0 otherwise
Borehole	Source of water for dairy animals is a borehole, equals 1 if yes, 0 otherwise
Well	Source of water for dairy animals is a well, equals 1 if yes, 0 otherwise
Milking parlour	Farm household owns a milking parlour, equals 1 if yes, 0 otherwise
Land owned (ha)	Total amount of farmland owned in hectares
Kabwe	Farm household is located in Kabwe, equals 1 if yes, 0 otherwise
Chibombo	Farm household is located in Chibombo, equals 1 if yes, 0 otherwise
Chongwe	Farm household is located in Chongwe, equals 1 if yes, 0 otherwise

The treatment variable is participation in ICAs, which equals 1 if the farmer participated in ICA in previous year and 0, otherwise. The outcome variables of interest are shown under the row titled outcome variables. These are the log of household income and log of milk revenue. Household income is the reported household income in Zambian Kwacha (ZMW) that was realised by the household during the 12 months before the survey. Milk revenue is defined as the monetary value obtained after multiplying the price of milk per litre by the quantity (litres) of milk sold. Milk was primarily produced by the dairy cows that were owned by households that participated in ICAs. The rest of the variables are independent variables used in the analysis. Table 2 presents the descriptive statistics of the variables used in the analysis.

Table 2. Descriptive statistics of selected variables used in the analysis.

(1)	(2)		(3)		(4)	
	Total sample		Participants		Non-participants	
Variable name	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Participation in ICAs	1.00		0.483		0.517	
Household income in ZMW	12,680.770	43,883.02	12,936.17	14,971.51	12,442.40	59,423.58
Milk revenue excluding missing values [a]	5496.87	11,383.86	8139.31	9072.42	3030.602	12,736.51
Explanatory variables						
Age (years)	50.847	13.607	52.561	13.068	49.248	13.963
Gender	0.931	0.254	0.918	0.275	0.943	0.233
Marital status						
Household size	5.099	2.180	5.122	2.267	5.076	2.106
Education	8.685	4.299	9.643	4.853	7.790	3.502
Dairy skills	0.793	0.406	0.888	0.317	0.705	0.458
Off-farm income in ZMW [b]	7187.640	42,572.650	4804.620	10,323.780	9411.800	58,399.880
Wealth index	−0.942	8.829	−4.032	10.963	1.941	4.680
Experience selling to MCC	2.700	4.688	5.449	5.384	0.133	1.366
Access to dairy information	0.596	0.492	0.796	0.405	0.410	0.494
Duration in farmer cooperation	3.049	4.924	5.520	5.417	0.743	2.932
Total livestock units (tlu)	9.311	8.580	10.940	10.367	7.790	6.157
Distance to MCC (km)	7.892	11.319	3.894	3.988	11.624	14.314
Distance to milk trader (km)	13.487	13.928	17.143	16.995	10.074	9.112
Proportion of milk sold	48.043	44.267	78.288	28.403	19.814	37.246
River	0.217	0.413	0.153	0.362	0.276	0.449
Dams-lake	0.044	0.206	0.071	0.259	0.019	0.137
Borehole	0.241	0.428	0.265	0.443	0.219	0.415
Well	0.497	0.501	0.510	0.502	0.485	0.502
Milking parlour	0.177	0.382	0.346	0.478	0.019	0.137
Land owned (ha)	9.275	19.820	11.328	26.601	7.358	9.763
Kabwe	0.187	0.391	0.285	0.454	0.095	0.294
Chibombo	0.586	0.493	0.448	0.499	0.714	0.453
Chongwe	0.226	0.419	0.265	0.443	0.190	0.394

Column (1) of Table 2 shows the variable names of all the variables used in the analysis. Columns (2–4) respectively show the means and standard deviations of the variables for the total sample, ICA participants and non-participants. Table 2 indicates that 48.3% of dairy farmers participated in ICA while the rest did not. Notably, milk revenue has about 41% missing values while the average age for ICA participants was about 53. Non-participants of ICAs were about 49 years old on average.

3. Modelling approach and estimation

3.1 Conceptual model

As it is common with contract farming, dairy farmers' participation in ICAs is not random. Treatment households either self-select themselves and/or are deliberately chosen based on their individual characteristics such as proximity to MCCs and herd size, or sometimes due to unobservable confounders (Bellemare 2012). Assuming the interest is to estimate the causal effect of participation in ICAs, *D* on the outcome of interest *Y* (i.e., household income in this study), there would be a fork between *D* and *Y*: an unobserved confounder *U* such as a farmer's industriousness or motivation that would affect both *D* and *Y*. We use directed acyclic graphs shown in Figure 1 to clearly demonstrate the effect of the unobserved confounder *U* on both *D* and *Y.* As shown in Figure 1, regressing *D* (ICA participation) on *Y* (household income) would be problematic because the causal effect of *D* on *Y* would be confounded by *U* (farmer's industriousness or motivation). It would be confounded because two pathways connect *D* and *Y*: (1) $D \to Y$ and (2) $D \leftarrow U \to Y$.

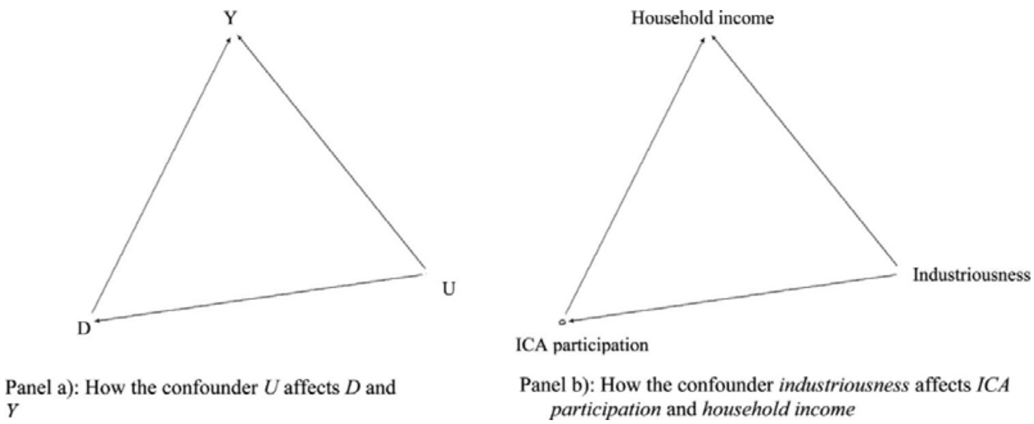

Figure 1. Directed acyclic graphs showing confounder effects.

While the two pathways generate statistical associations between *D* and *Y*, only path 1 would be causal (McElreath 2020). The second path is not causal but only produces an association between *D* and *Y* (i.e., between ICA participation and household income) through the backdoor of *D*. If path 2 was the only path available, any change in *D* would not affect *Y* which suggests that the unbiased causal effect of *D* on *Y* operates only through path 1. Otherwise, one would alternatively and statistically adjust the effect by *U,* but *U* is unobservable. A suitable IV would allow us to estimate the correct causal effect of *D* on *Y*. Let *Z* (e.g., access to dairy information) be an IV. The variable access to dairy information or *Z* would act as a natural experiment on participation in ICAs, *D*. As shown in the directed acyclic graph in Figure 2, technically, access to dairy information would be an IV if it were independent of industriousness or motivation (i.e., *U*), not independent of participation in ICAs, and would not influence *Y* (household income) except through ICA participation, *D*. That *Z* would not influence *Y* except through *D* is a well-known exclusion restriction condition.

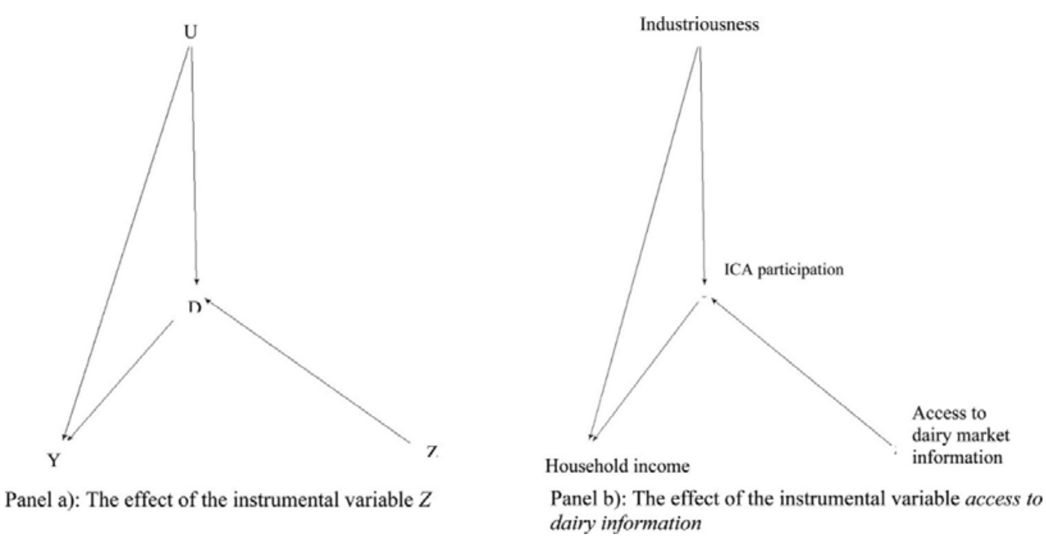

Figure 2. Directed acyclic graphs showing the effect of the instrumental variables.

A closer look of Figure 2 shows that *Z* (access to dairy information) satisfies all the criteria for a suitable IV for *D* (ICA participation). This way, the causal chain would be established and the causal effect of *D* that is uncontaminated by unobservable effects *U* would be the treatment effect to *Y* (Shi and Tong 2020; McElreath 2020). Wooldridge (2002) and Angrist and Pischke (2008) call the partial effect estimated here as the local average treatment effect (LATE).

Consider a continuous treatment variable. Also, let $\boldsymbol{Z_i} = (Z_{i1}, \ldots, |Z_{iJ})'$ be a vector of IVs where *J* is the number of instruments. The IV approach would traditionally involve estimating two equations. The first stage would involve using Z_i to estimate and identify the portion of ICA participation *D*. The second stage would rely on the estimated exogenous portion of *D*'s variations in the form of predicted treatment values to estimate the

LATE. Mathematically

$$D_i = \beta_{10} + \beta_{11} \boldsymbol{Z_i} + \epsilon_{1i} \tag{1}$$

$$\boldsymbol{y_i} = \beta_{20} + \beta_{21} \widehat{\boldsymbol{D}}_i + \epsilon_{2i} \tag{2}$$

where β_{10} and $\beta_{11} = (\beta_{11},\ldots,\beta_{1J})'$ are first-stage regression parameters, β_{20} and β_{21} are second-stage regression parameters, $\widehat{D}_i$ is the i^{th} observation of the predicted treatment value while error terms would be assumed to be Gaussian distributed as ϵ $\epsilon_{1i} \sim N(0,\ \sigma^2_{\epsilon 1})$ and $\epsilon_{2i} \sim N(0,\ \sigma^2_{\epsilon 2})$. The coefficient β_{11} is the causal effect of *Z* on the ICA participation *D* while β_{21} is the LATE – which is the goal of this research.

3.2 Empirical model

The use of IVs has been effective at mitigating selection bias in impact evaluation research. This paper uses a robust two-stage Bayesian estimation approach proposed by Shi and Tong (2017, 2020) to estimate the LATE. Consider D_i and y_i as participation in ICAs and household income, respectively, for the i^{th} farm household. Because our treatment variable – participation in ICAs is categorical, mathematically the generalised two-stage

causal model is

$$D_i \sim \text{Bernoulli}(p_i) \quad 3)$$

$$\text{logit}(p_i) = \beta_{10} + \beta_{11} \boldsymbol{Z_i} \tag{4}$$

$$\boldsymbol{y_i} = \beta_{20} + \beta_{21} \widehat{\boldsymbol{p}}_i + \epsilon_i \tag{5}$$

where β_{10} and $\beta_{11} = (\beta_{11},\ldots,\beta_{1J})'$ are first-stage regression parameters for the logistic regression model in which the logit of the probability that a dairy farmer participates in ICAs is regressed on the IVs Z_i. Farmer participation in ICAs D_i follows a Bernoulli distribution with p_i being the probability that $D_i = 1$ if the dairy farmer participates in ICAs, and $D_i = (1 - p_i)$, otherwise.

Traditionally, the residuals from equation (5) are assumed Gaussian distributed, though empirical data usually violate the Gaussian assumption because they may have heavy tails or contain outliers (Shi and Tong 2020). Several approaches have been developed to deal with these data problems (see: Zhong and Yuan 2010; Hampel et al. 1996, and Huber 1981, for more details). Lee and Xia (2006) and Lange, Little, and Taylor (1989) developed robust methods based on Student *t* distributions, whereby extreme values in the data can be down-weighted. Shi and Tong (2017; 2020) extended the use of Student *t* distributions by incorporating IVs in a Bayesian framework. Because our treatment variable is categorical, we use Shi and Tong's (2017, 2020) cat-normal model in our estimation where the outcome variable is the log of household income. However, as shown in Table 2, milk revenue has missing values. This indicates that some dairy farmers in our sample skipped the question about how much milk revenue they realised.

Our case may be similar to when respondents with high income would less likely report the income or as Shi and Tong (2020) put it; that people may fail to fill in a depression-related survey because of their depression levels. Thus, missing values of milk revenue could be due to unobserved underlying factors. As Gelman et al. (2013) and McElreath (2020) suggest, missing data have value in research and should not be given zeros or thrown out of the analysis. Following Rubin (1976), we consider the missing data on milk revenue as a non-ignorable missing problem. Ignorable missing data are dealt with using multiple imputation techniques in which unbiased and efficient parameter estimates are obtained (Allison 2003; Enders and Bandalos 2001; Gelman et al. 2013; McElreath 2020). Additionally, implementing multiple imputation in Bayesian analysis is a natural phenomenon (Shi and Tong 2020) since all parameters are random and missing data are treated as additional parameters. Bayesian Markov chain Monte Carlo (MCMC) methods iteratively impute estimates of missing values based on the distribution of missing values.

To account for missing milk revenue values, we estimate a Bayesian cat-robust-selection model proposed by Shi and Tong (2017, 2020). Shi and Tong (2017, 2020) suggest the inclusion of the probit link in the second stage of estimation of the system of equations (3–5). Mathematically, the model is

$$D_i \sim \text{Bernoulli}(p_i) \quad 6)$$

$$\text{logit}(p_i) = \beta_{10} + \beta_{11} \boldsymbol{Z_i} \quad (7)$$

$$\boldsymbol{y_i} = \beta_{20} + \beta_{21} \widehat{\boldsymbol{p}}_{\boldsymbol{i}} + \epsilon_i \quad (8)$$

$$R_i \sim \text{Bernoulli}(q_i) \quad (9)$$

$$q = \Phi(\xi_0 + \xi_1 \boldsymbol{y_i}) \quad (10)$$

where variables in equations (6–8) are as discussed before, while R_i is a missing indicator for theobservation and equals 1 if missing, 0 otherwise. R_i follows a Bernoulli distribution with q_i being the probability that y_i (i.e., the i^{th} log of milk revenue) is missing, Φ is the cumulative Gaussian distribution function, ξ_0 and ξ_1 are parameters to be estimated in the missing data selection equation, and $\epsilon_i \sim t(0,\ \sigma_\epsilon^2, v)$.

For model estimation, we use Bayesian methods for reasons stated previously as well as for our low sample size and the missing values of *milk revenue*. Bayesian analysis involves estimation of the joint posterior according to Bayes' rule which states that such a posterior is proportional to the product of prior distribution of parameters and the likelihood function. As in Ng'ombe and Boyer (2019), we used the usual conditionally conjugate and diffuse priors for all model parameters including the LATE parameter so that our priors would negligibly affect the results. This is common with Gibbs sampling and Metropolis-Hastings algorithms (Gelman et al. 2013). We use Gibbs sampling in all estimations rather than Metropolis-Hastings because it is more efficient than the latter, which potentially generates highly correlated draws (Ntzoufras 2011).

Since a Student *t* distribution can be viewed as a Gaussian distribution whose variance parameter is weighted by a Gamma distribution, data augmentation can be used to simplify the generation of posterior distributions of the parameters. Following Shi and Tong (2017) and Press (1972), a random variable ω_i is augmented with a Gaussian distributed random variable if $\omega_i \sim G\left(\frac{v}{2}, \frac{v}{2}\right)$ and $\boldsymbol{y}|\omega_i \sim N\left(\mu, \frac{\Psi}{\omega_i}\right)$, which implies then $\boldsymbol{y_i} \sim t(\mu,\ \Psi,\ v)$. All our MCMC techniques involved 2 chains with a warm-up phase of 150,000 to ensure the Markov chains forget their starting states (Gill 2014; Ng'ombe, Tembo, and Masasi 2020; Ng'ombe and Brorsen 2020), with total iterations of 300,000 per chain. These simulations were conducted in BayES, R software and OpenBUGS (Sturtz, Ligges, and Gelman 2005; Emvalomatis 2020; Shi, Tong, and Meyer 2020; R Core Team 2020). To check whether the MCMC chains converged successfully to their target posterior distributions, we conducted a convergence diagnostic test by Gelman and Rubin (1992). The Gelman-Rubin test checks if posterior samples are stationary, by comparing the intra-and inter-chain variations. If the test statistic for all parameters is less than 1.10, convergence is successful; otherwise, it is not (Gelman and Rubin 1992; Gelman et al. 2013; Ng'ombe and Brorsen 2020). For all our estimations and the parameter estimates, the Gelman–Rubin test statistics were equal to 1.00, which provides strong evidence of convergence.

4. Estimation results and discussion

4.1 Determinants of dairy farmers' participation in ICAs

For our first objective, we estimated a Bayesian logistic regression model whose marginal effects are presented in Table 3. To save space, the original parameter estimates are in Table A2 in the Appendix. The marginal effects in Table 3 are evaluated at the means of independent variables. They can be interpreted as the change in probability of participating in ICAs with respect to a change in the respective independent variable (in case of continuous independent variables). For independent variables that are dummy variables, they imply a change in the probability to participate in ICAs as a result of a discrete change from 0 to 1; everything else held constant. In terms of significance of the results, we interpret the estimated parameter estimates as significant if their respective Bayesian credible intervals do not span zero.

Table 3. Marginal effects of determinants of participation in dairy sector ICAs.

(1) Variable name	(2) Posterior mean	(3) Std. Dev	(4) Bayesian 90% credible interval	
Dep. variable is ICA participation				
Age	−0.003	0.002	−0.007	0.000
Gender	0.179	0.081	0.050	0.317
Single	0.042	0.076	−0.096	0.148
Household size	−0.009	0.016	−0.035	0.015
Education	−0.014	0.010	−0.033	0.001
Log of off-farm income	−0.057	0.024	−0.101	−0.022
Dairy skills	−0.072	0.048	−0.140	0.008
Wealth index	0.029	0.015	0.009	0.056
Experience selling to MCC	0.176	0.050	0.094	0.261
Duration in farmer cooperation	0.002	0.010	−0.015	0.018
Livestock holding (tlu)	0.013	0.007	0.004	0.027
Crossbreeding management	−0.005	0.074	−0.112	0.109
Milking parlour	0.231	0.091	0.093	0.391
Access to dairy information	0.319	0.108	0.150	0.504
Distance to MCC	−0.026	0.014	−0.053	−0.008
Land owned (ha)	0.010	0.005	0.003	0.018

Results in Table 3 suggest that compared to women-headed households, male-headed households are about 18% more likely to participate in ICAs, everything else held constant. This result is consistent with Bellemare (2012) who finds that male-headed households are 45% more likely to participate in crop sector contract farming arrangements in Madagascar. Similar findings have also been reported by the World Bank (2008), Belay (2020), and Mulungu and Mudege (2020). Results in these three studies suggest that gender norms and practices persistent in most African societies may constrain women's economic capabilities and participation in most market institutions. As for off-farm income, we find that an increase in off-farm income reduces the probability of participating in ICAs among dairy farmers in Zambia. This finding is consistent with Kiwanuka and Machethe (2016) and is plausible because, engaging in off-farm income generating activities may take away the time farmers would need to devote to ICAs – thereby making them less likely participate in the institution.

We further find that increase in wealth, years of selling to MCCs, and having more livestock increases the probability of dairy farmers' participation in ICAs. Wealthier farmers would easily deliver high-quality milk to contractors as they may have such equipment as refrigerators and the transport to deliver the output than otherwise. Similarly, farmers with increased years of experience selling to contractors may have established strong trust and relationship with contractors. These are crucial for the success of these market-based institutions (Belay 2020). Moreover, we find that farmers with more livestock are more likely to participate in ICAs. We expect that having more livestock is a sign of wealth and could be associated with having more dairy animals, and therefore more milk would have to be sold. Since contract farming is claimed to be an attractive resource that links farmers to markets (Barrett et al. 2012), it is reasonable for farmers with more dairy animals to likely participate in ICAs hoping they would find a milk market for large quantities of milk produced. We find that dairy farmers who own a milking parlour are on average about 23.1% more likely to participate in ICAs than otherwise, and this value ranges between 9.3% and 39.1% with 90% probability. This is plausible because milk parlours are expected to increase milk production (Jacobs and Siegford 2012) that would require a wider market, and ICAs may be an attractive opportunity to bring such markets closer.

Dairy farmers with access to dairy marketing information are about 32% more likely to participate in ICAs than otherwise. This is expected *a priori* as farmers with access to such dairy marketing information as prices, product quality and quantities, distribution schedules would be more aware of the available market opportunities and risks. This way, they would be better positioned to participate in the institution than otherwise (Kiwanuka and Machethe 2016; Olounlade et al. 2020).

Location of a farm household by an extra kilometre away from MCCs is associated with a 2.6% likelihood of a farm household to participate in ICAs. This finding suggests that dairy farms located in remote areas are less likely to participate in ICAs – a challenge that limits farmers' participation in contract farming arrangements in developing countries (Narayan 2010; Wainaina, Okello, and Nzuma 2012; Kiwanuka and Machethe 2016). Long distances may increase transportation costs and affect milk quality, especially during the hot season because smallholders in developing countries may not have adequate refrigerators that milk requires. Actually, Kiwanuka and Machethe (2016) suggest dairy cooperatives such as the Chibombo dairy cooperative in Zambia requires that farmers should be within a 50 km radius from the MCC to participate in ICAs – which would discourage many farmers located in rural areas from participating in ICAs. Moreover, due to remoteness and impassable roads in Zambia, it is plausible that the dairy farmers located in these areas may have limited access to extension services (Ng'ombe, Kalinda, and Tembo 2017).

Furthermore, an extra amount of hectares of farmland owned by a dairy farmer increases their probability of participating in ICAs by 1%, a value that ranges between 0.3% and 1.8% with 90% probability. Owning more land implies that a farm household may have more pasture-land to allocate to dairy animals, thereby increasing the quantity of milk produced and subsequently increasing the households' chance of selling milk through ICAs.

4.2 Impacts of participation in ICAs on milk revenue

A simple falsification test proposed by Di Falco, Veronesi, and Yesuf (2011) to determine the suitability of IVs reveals that our instruments are valid. These are variables that would affect farmer's participation in ICAs but would not affect the respective outcome variables (log of household income or log of milk revenue) for dairy farmers that did not participate in ICAs. The selected IV used in modelling causal effects of participation in ICA on the log of household income was access to dairy information while the distance to milk collection centres was used when the outcome variable was the log of milk revenue. While a simple falsification test (Di Falco, Veronesi, and Yesuf 2011) used here has been widely used to determine the suitability of instruments in most impact evaluation studies (e.g., Ding and Abdulai 2020; Manda et al. 2019; Ng'ombe, Kalinda, and Tembo 2017; Di Falco and Veronesi 2013, and others), it does not mean our instruments are perfect. Some studies on contract farming have used the distance between a respondent's farm and the village chief's farm (Miyata, Minot, and Hu 2009), membership in a farmer group (Rao and Qaim 2011) as suitable IVs for contract farming participation. But as pointed out by Bellemare (2012), it is unobvious how the selected IVs in previous papers allow the reduction of the endogeneity problem – which again suggests that our IVs are not perfect. However, all the first-stage regressions indicate that our selected IVs are significantly strong. This implies that one should not be overly concerned with selection bias at least in all estimations, appearing in this study. This, coupled with robust

Bayesian methods used here, our identification strategy should represent an important step in the right direction at modelling the welfare effects of ICAs in the dairy sector and others.

Table 4 presents posterior means of all the mathematical model parameter estimates in equations (6–10). As before, columns (1), (2) and (3) respectively report variable names, posterior means, and standard deviations. Column (4) presents Bayesian 95% credible intervals for respective posterior means. First stage regression results indicate that distance to MCC is a strong instrument for estimating causal effects of ICA participation on milk revenue. An increase in the distance to MCC from a farmer's household is associated with a lower likelihood of a dairy farmer's participation in ICAs, which is plausible, as was discussed previously.

Table 4. Posterior results for impacts of ICA participation on milk revenue.

(1) Variable name	(2) Posterior mean	(3) Standard deviation	(4) Bayesian 95% credible interval	
First-stage results: dep. variable is ICA participation			2.5%	97.5%
Intercept	0.910	0.253	0.425	1.420
Distance to MCC	−0.168	0.042	−0.254	−0.092
Second-stage results: dep variable is log of milk revenue				
Intercept	5.911	0.500	4.924	6.888
Age	0.005	0.004	−0.004	0.014
Gender	−0.029	0.218	−0.458	0.400
Marital status	0.644	0.455	−0.261	1.533
Household size	0.024	0.028	−0.030	0.078
Education	0.065	0.019	0.029	0.102
Log of off-farm income	0.127	0.021	0.086	0.169
Dairy skills	−0.255	0.152	−0.552	0.043
Wealth index	0.015	0.013	−0.011	0.040
Experience selling to MCC	0.001	0.019	−0.038	0.036
Duration in farmer cooperation	0.004	0.018	−0.031	0.039
Livestock holding (tlu)	0.027	0.009	0.009	0.045
Crossbreeding management	0.346	0.177	−0.001	0.693
Proportion of milk sold	0.015	0.002	0.012	0.018
Milking parlour	0.299	0.211	−0.120	0.706
River	0.100	0.145	−0.187	0.384
Dams lake	−0.203	0.264	−0.720	0.320
Borehole	−0.086	0.150	−0.381	0.211
Land owned (ha)	0.006	0.004	−0.001	0.016
Local average treatment effect (LATE)	−0.346	0.323	−1.01	0.263
Missing data selection model				
Intercept	4.468	0.654	3.188	5.812
Slope	−0.557	0.077	−0.715	−0.407
Sigma squared	0.444	0.078	0.308	0.612
Estimated degrees of freedom	5.937	3.084	2.933	12.51
Deviance	959.455	7.775	946.3	976.7

Second-stage results in which the dependent variable is the log of milk revenue reveal that age, marital status, and gender of the household head do not have significant effects of affecting ICA on milk revenue. A similar finding exists for household size. However, the level of education of the household head significantly increases milk revenue through ICA participation by about 6.5% and this result ranges between 2.9% and 10.2% with a probability of 0.95, holding other factors constant. More educated farmers involved in ICAs would more likely take advantage of existing opportunities to optimise payoffs involving ICAs.

Off-farm income also has positive causal effects on milk revenue through ICA participation. Following Bellemare (2012), farmer's willingness to participate in contract farming in Madagascar was dependent on whether the farm household had sufficient working capital given the stringent requirements of contracted crops compared to other crops. Similarly, dairy farmers contracted to provide milk face stricter requirements and having enough off-farm income would be one way to boost milk revenue through ICAs by enabling farmers to acquire the necessary agricultural equipment to aid their operations and maintain the milk quality.

The number of livestock animals that farmers possess has significant positive effects of affecting ICA participation on milk revenue – an unsurprising result. Dairy farm households with more livestock, most of which should be dairy animals would more likely produce more milk and boost milk revenue. Similarly, farmers who sell larger milk proportions they produce would have significant positive effects of affecting ICA participation on milk revenue, when all other factors are held fixed. The impact of ICA participation is captured by the LATE estimate in Table 4 . In general, participation in ICAs by smallholder dairy farmers is associated with a 34% reduction in milk revenues, though this finding is not significant.

Our finding can be attributed to many potential factors. For example, during the survey, one of the processors intimated that MCC leaders were exploiting the rest of the members and ripping them off their hard-earned monies through exorbitant charges. Whereas some MCCs charged a commission as low as 0.1 ZMW/litre of milk supplied by farmers, others charged as high as 0.6 ZMW/litre. Although the commission goes towards meeting the high costs incurred by MCCs at ensuring that a high-quality product is delivered to the processors, it likely lowers the effective price received by farmers. For instance, the effective price received by dairy farmers ranges from 2.5 to 3.4 ZMW/litre, which is sometimes lower than the 3.5 ZMW/ litre received on the spot market. As such, there is a strong incentive to side sell milk to other buyers rather than the MCCs, since the former is more profitable. From our experience, side selling in Zambian ICAs is possible because other customers buy milk from the farm which implies that farmers do not have to incur any transportation costs in delivering milk to the market. This suggests that ICAs in Zambia might not be free from being misaligned with transaction attributes, hence they may be prone to inefficiency (Mugwagwa, Bijman, and Trienekens 2020). In other words, there is a chance that dairy farmers do not loyally deliver milk to their buyers according to contracts, most probably to cut down transactions costs such as transportation and refrigeration. Actually, while side-selling may be economically irrational, it remains a reasonable decision from a farmer's livelihood perspective point of view (Mujawamariya, D'Haese, and Speelman 2013). Nonetheless it deeply affects the longevity and sustainability of ICAs (Mujawamariya, D'Haese, and Speelman 2013; Zhang 2012) which could be a reason for the negative impacts on milk revenue. As pointed out by Mujawamariya, D'Haese, and Speelman (2013), dealing with potential side-selling in ICAs involves contractors to rethink about their relationship with farmers by reducing transactions costs and incentivizing to produce more and better quality milk.

Moreover, it is noteworthy to mention that these results may seem surprising especially that descriptive statistics indicate that ICA participants realise ZMW8139.1 ($814) while their counterparts realise ZMW3030.6 ($303) from milk revenue. However, these are only descriptive statistics – they are simplistic and are potentially subject to loss of nuance or detail (Wheelan 2013; Ng'ombe, Tembo, and Masasi 2020). They do not account for other sources of the unobserved confounders. In fact, milk revenue had about 41% missing rate, which led us to use a categorical robust-selection model, proposed by Shi and Tong (2017; 2020).

Shown below the LATE estimate in Table 4 are results of the missing data selection model which correspond to equation (10) in the main body of the paper. Results indicate that dairy farmers that realise higher milk revenue would less likely report missing milk revenue values than those with less income. This finding is significant implying that accounting for the missing values was appropriate. Without accounting for ignorable missingness or throwing away missing data would obviously bias our findings. Thus, our results indicate that while ICAs seem promissory to resolve persistent market failures and improve smallholder farmers' welfare in developing countries as found by some previous studies in the crop sector (e.g., Miyata, Minot, and Hu 2009; Bellemare 2012; Barrett et al. 2012), they do not show similar results in the dairy sector – especially for developing countries like Zambia.

In other words, participants in ICAs are probably unable to benefit from spillover effects associated with an increase in milk revenue because of the nature of dairy farming, which is labour-intensive and requires adequate capital investment that is a significant challenge for smallholder farmers (Douphrate et al. 2013). Coupled with the additional workload required to meet the stringent milk quality standards set by the processor, smallholder dairy farmers may subsequently be unable to diversify their livelihoods to enhance their household income. Hence, these findings somehow contradict the notion that smallholder farmers' participation in contract farming enhances household incomes (Alemu et al. 2016; Mwambi et al. 2016).

4.3 Impacts of participation in ICAs on household income

Table 5 presents the estimation results of the impact of ICA participation on the log of household income. Column 1 reports model variables while columns 2 and 3 present their respective posterior means and standard deviations. Column 4 presents the 95% Bayesian credible intervals for each posterior mean value in column 2. As mentioned previously, first-stage regression results (corresponding to equation (4)) suggest the selected IV (i.e., access to dairy marketing information) is a strong instrument for modelling the impact of ICA participation on household income because it significantly affects participation in ICAs. Like other studies (e.g., Khonje et al. 2015; Khonje et al. 2018; and Olagunju et al. 2019), access to information has been widely used to instrument farmers' adoption/participation decisions in various institutions.

Table 5. Posterior means for impact of ICA participation on household income.

(1) Variable name	(2) Posterior mean	(3) Std. Dev	(4) Bayesian 95% credible interval	
First-stage results: dep. variable is ICA participation				
Intercept	−1.116	0.261	−0.938	−0.621
Access to dairy marketing information	1.696	0.326	1.913	2.345
Second-stage results: dep variable is log of household income				
Intercept	5.402	0.530	4.344	6.434
Age	0.006	0.005	−0.004	0.016
Gender	0.026	0.260	−0.478	0.541
Marital status	0.625	0.488	−0.332	1.585
Household size	0.017	0.032	−0.045	0.080
Education	0.074	0.021	0.034	0.114
Log of off-farm income	0.151	0.023	0.106	0.196
Dairy skills	−0.108	0.180	−0.459	0.246
Wealth index	0.015	0.015	−0.014	0.044
Experience selling to MCC	−0.007	0.022	−0.050	0.036
Duration in farmer cooperation	0.002	0.020	−0.038	0.042
Livestock holding (tlu)	0.026	0.010	0.007	0.046
Crossbreeding management	0.459	0.208	0.051	0.869
Proportion of milk sold (%)	0.015	0.002	0.011	0.019
River	0.157	0.165	−0.165	0.48
Dams-lake	−0.107	0.328	−0.751	0.533
Borehole	0.097	0.171	−0.236	0.433
Milking parlour	0.165	0.241	−0.308	0.635
Land owned (ha)	0.006	0.003	−0.001	0.012
Local average treatment effect (LATE)	−0.223	0.443	−1.129	0.635
Sigma Squared	0.779	0.082	0.634	0.956
Deviance	774.955	7.123	763	790.800

Moreover, that access to dairy marketing information positively affects smallholder dairy farmers' participation in ICA is an important finding because it highlights the importance of access to information on farmers' behaviour toward some technology or institution that would, later on, affect their welfare. This finding is not surprising because dairy farmers with access to marketing information are more likely to be aware of the available market opportunities and threats. Thus, they would be more likely to make a rational decision about their association with ICAs (Kiwanuka and Machethe 2016; Olounlade et al. 2020).

Our second-stage results correspond to equation (5) in the body of the paper. Results show that age, marital status, and gender of the household head, as well as household size, do not have significant effects of affecting dairy farmers' participation in ICAs, on their household income, *ceteris paribus*. However, results indicate that everything else held constant, a one-year increase in the number of years of education by a farm household head is on average associated with 7.4% increase in household income through ICA participation, a value that ranges between 3.4% and 11.4% with 95% probability. This finding is expected because farmers with more education would perhaps have more income sources aside from participating in ICA. For example, Kuntashula, van der Horst, and Vermeylen (2014) posit that more educated farmers are more likely to engage in multiple income-generating activities resulting in increased household incomes, one of which in our case could be ICA participation. Lubungu, Chapoto, and Tembo (2012) observe that additional years of education among smallholder livestock farmers increase their ability to profitably utilise both market information and market opportunities which could be the case for farmers involved in ICAs.

As expected, we find that the amount of off-farm income a dairy farm earns has significant positive effects of affecting ICA participation on dairy farmers' household income. Specifically, a 1% increase in off-farm income among dairy farm households is associated with an average 15.1% rise in household income through ICA participation, and this value ranges between 10.6% and 19.6% with a probability of 0.95, *ceteris paribus.* Off-farm income can be used to purchase farm equipment as well as more dairy inputs to boost a farmer's participation requirements in ICA that could affect household income. Unexpectedly, we find that farmer's knowledge of dairy skills, wealth index, experience at selling milk to MCCs, and their length of belonging to a farmers' cooperation do not have significant effects of affecting ICA participation on household income.

Nonetheless, results suggest that everything else held constant, the more livestock a farmer has, the more likely would this affect ICA participation to increase household incomes. This is unsurprising because livestock is a source of wealth and could play a key role in affecting ICA participation's effects on household income. Livestock is reared for different purposes that include cash, meat, milk, manure, draught power and traditional ceremonies (Lubungu, Chapoto, and Tembo 2012) that would eventually boost household income among ICA participants. Crossbreeding livestock and increasing the proportion of milk sold have significant positive effects on ICA participation on household incomes. However, the type of water sources (river, dams-lake and borehole, relative to a well) for livestock, ownership of a milking parlour and total land size do not have meaningful effects of affecting ICA participation on household incomes. While establishing the mechanisms through which ICA participation may affect income is beyond this paper's scope, the second-stage regression findings may represent such mechanisms – however, this is merely hypothetical.

The impact of ICA participation on household incomes is captured by the posterior mean of the LATE estimate in Table 5 . Results indicate that, on average, dairy farmers' participation in ICAs negatively affects their household income. However, the effect is not significant. This is as illustrated by the LATE's 95% credible interval that spans zero. This finding is consistent with Bellemare (2012) who finds non-significant effects of contract farming on household income per adult equivalent from the livestock sector in Madagascar. Contrary to our results, Rao and Qaim (2011), Bellemare (2012) and Minten, Randrianarison, and Swinnen (2009) suggest smallholder farmers in the crop sector could benefit from contract farming, but only through better access to inputs and technology that would lead to higher and stable incomes. However, Saenger et al. (2013) suggest that smallholders may struggle to meet stringent quality standards leading to their underinvestment in their production – which Zambian dairy farmers involved in ICAs may not be an exception (Namulindwa 2018). Thus, while ICAs are a useful institution that can facilitate smallholder market participation, commercialisation, improved household welfare, and rural development (Meemken and Bellemare 2020), our findings indicate that the institution may not yet be fully capable to deliver expected positive results on dairy farmers' welfare in a developing country like Zambia.

5. Conclusions and policy implications

This paper analyses the determinants of dairy farmers' participation in interlocked contractual arrangements (ICAs) as well as the impact that ICAs have on farmers' welfare. We use data collected from smallholder dairy farmers in Zambia. It is the first study to deliver a useful empirical application of a robust two-stage Bayesian instrumental variable approach on contract farming, to account for potential selection bias of farmers' participation in ICAs, non-Gaussian data and missing data problems. The methods used here are cutting-edge as they also account for potential non-Gaussian and missing data which are prevalent in empirical research. Rather than using alternative approaches, our modelling is under a Bayesian framework because it is exact in any sample size (Gelman et al. 2013; Ng'ombe and Boyer 2019; McElreath 2020; Shi and Tong 2016; 2020) and delivers posterior distributions of model parameters thereby accounting for uncertainty in both data and model parameters.

The following conclusions and policy implications can be drawn from this study. First, results suggest that dairy farmer's participation in ICAs is positively affected by male gender of the household head, wealth, experience selling to milk collection centres (MCCs), livestock holding, ownership of milk parlour, landholding and access to dairy marketing information. However, increased off-farm income and distance to milk collection centres significantly decrease the probability of dairy farmers to participate in ICAs. Taken together, these results can be used to target policies aimed at incorporating more dairy farmers in ICAs by ensuring that MCCs are also built in remote areas. Subsidising access to livestock, fostering access to dairy marketing information among farmers would be helpful if promoting ICA participation is the goal for relevant stakeholders. Second, whereas participation in contract farming is perceived to deliver positive results on household incomes and that we found several factors that affect participation in ICAs, this paper shows that participation in ICA does not improve household incomes in the dairy sector. Actually, we found that the dairy farmer's participation in ICAs reduces household income by about 22%, though this result is not significant.

Third, while the direct outcomes from ICAs in the dairy sector are through improved milk revenue, ICA participation reduces milk revenue by about 34%, even though this finding is also not significant. The policy implication of these results is that there is no sufficient evidence of causal effects of ICAs on household incomes and milk revenue among dairy farmers in Zambia. Therefore, policy makers in Zambia and other developing countries need to re-examine the performance of the entire contract farming institution in the dairy sector because it may not be achieving the intended goals. There may be need for processors (powerful buyers) to ensure that they use their power judiciously to create a more integrated value chain that benefits both themselves and their suppliers. Involving dairy farmers in key business decision-making processes would be a good starting point. Frequent review of the memoranda of understanding is important because the business environment in which dairy farmers operate is very dynamic. Rewarding dairy farmers appropriately by offering them a net milk price that considers the fact that farmers incur additional costs in supplying a higher quality product to processors than to the spot market should be encouraged. This would probably go a long way at cushioning farmers from the effect of inflation and motivate them to sell more milk through ICAs. Another alternative would be for processors to pay milk suppliers bonuses at the end of each accounting period especially when they make more profit than anticipated. Additionally, it is also important that milk buyers and smallholder dairy farmers build trust in their exchange relationships, since trust yields commitment to long-term relationships and enhances value chain performance (Belay 2020; Ruml and Qaim 2020; Kiwanuka and Machethe 2016).

Fourth, our results show that more educated farmers, increased proportion of milk sold to MCCs, and increased number of livestock owned have significant positive effects affecting ICA participation on household income and milk revenue. This suggests the need for more extension services to train smallholder dairy farmers about how ICAs can work to their advantage as well as how farmers could invest in more dairy livestock to boost milk production. This way, perhaps the potential benefits of contract farming as perceived in the crop sector (Bellemare 2012; Minten, Randrianarison, and Swinnen 2009; Rao and Qaim 2011; Saenger et al. 2013) could also be realised in the dairy sector.

Following Bellemare (2012), the alternative approach would be for policy makers to stimulate participation in ICA by subsidising acquisition of dairy animals among farmers. This is because most ICA participants considered in this study were less wealthy than their counterparts as indicated by their most negative mean wealth index in

. Thus, smallholder dairy farmers participating in contract farming may not have adequate capital investment required for them to meet the quality challenges of contract farming (Douphrate et al. 2013). That ICA non-participants were wealthier than participants (at least in our data) – is an indication that ICAs are inclusive of resource-poor dairy farm households. In general, as much as the public sector and other stakeholders emphasise ICAs, there is a need for reorientation of support from over-emphasis on contract farming among dairy farmers to a mix of other strategies, such as linking farmers to other formal and informal markets and promotion of livelihood diversification.

More generally, the overall question that remains is why would smallholder dairy farmers still participate in ICAs even if there are no positive results? Plausibly, participation in these contracts is also motivated by unobservable factors (Bellemare 2012) such as motivation, hope and others. Similarly, smallholder dairy farmers in developing countries may cling on to ICAs with the hope that they would somehow and eventually realise the benefits. Smallholder dairy farmers may hope that the number of dairy animals would increase and hope to produce more milk with time, and therefore consider their current participation as a foundation for future benefits. Additionally, the decision to switch and walk away from the contracts may be not trivial as there could be switching costs such as lawsuits against farmers that abrogate contracts (FAO, IFAD, UNIDROIT 2017). Most ICAs are binding and may attract penalties for abrogation, which could be why farmers remain in the institution despite negative welfare outcomes. For example, Ruml and Qaim (2020) report that most oil palm contracted farmers in Ghana regret their decision to participate in the contract farming scheme and would prefer to exit if they could. Thus, the existence of transaction-specific investments such as bulk cooling facilities, milk processing plant and transport (refrigerated trucks) in contract dairy farming also represents high switching costs. However, Namulindwa (2018) suggests that these switching costs may enable both the off-taker and smallholder farmers to experience more repeat business and less variability in sales volume and income, which could in turn lower the risk of farmers and help curb opportunism in the current exchange relationship.

As is the case with empirical work, we qualify our empirical findings by offering a few caveats. First, while the instrumental variables (IVs) used in this paper are valid as shown by several tests (falsification test and first-stage regression results), readers should know that they are not perfect. However, our identification strategy should represent an important step in the right direction in modelling the welfare effects of institutions/technologies that involve non-random selection of respondents. Second, we found non-significant negative effects of ICAs on household welfare. But we do not establish the mechanisms through which this happens. Admittedly, this is beyond the scope of our study. However, it is an interesting empirical question for future research. Third, our data are cross-sectional and we suggest future research should use richer multi-year (longitudinal) data that would perhaps provide more insights on the dynamics of contract farming and its welfare effects in the dairy sector. Additionally, while we have used household income as a proxy for welfare, household income is more prone to under-reporting and it does not take into account the various costs borne by the household. Instead, using farm profits (which were not part of our data set) would constitute a much better measure of welfare for future research.

Acknowledgments

The authors are grateful to African Economic Research Consortium (AERC) for funding this research. They also acknowledge the anonymous reviewers and Editor-in-Chief, Professor Johann Kirsten for comments and suggestions on earlier drafts of this paper. All errors are the responsibility of the authors.

Disclosure statement

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

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