Spilt Milk: Measuring the Indirect Effects of Livestock Ownership in Rural Zambia

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1 Introduction

The United Nations Food and Agriculture Organization (FAO) estimates that 815 million people worldwide suffer from chronic hunger, which is defined as insufficient food intake to meet dietary energy requirements. In Eastern Africa, it is estimated that nearly a third of the population is affected. Malnutrition, which includes undernourishment, overnutrition, and specific micronutrient deficiencies, has led to simultaneous observance of obesity, stunting, wasting, and anaemia. Children have been particularly affected across the globe: approximately 155 million under the age of five suffer from stunting (low height for age) and 51.7 million suffer from wasting (low weight for height) (FAO et al., 2017).

Deficiencies in macronutrients such as protein and micronutrients like vitamin A and iron, have been shown to relate to health, nutrition, and productivity outcomes later in life (Hoddinott et al., 2015; Victora et al., 2008). Animal-source foods (ASFs) are the most prevalent source of these nutrients, and thus programs to increase the quantity of animal products available for consumption have been deployed in the developing world (Whaley et al., 2003). Livestock ownership can affect nutrition outcomes in multiple ways: through increased availability of dairy or meat products, and through increased household income leading to increased consumption (Nicholson et al., 2003; Jodlowski et al., 2016; Kafle et al., 2016). The identification of the causal impact of livestock ownership has been hindered by endogeneity in the decision to own livestock. Using data from the staggered rollout of a Heifer International (HI) livestock donation in Zambia, this paper contributes to literature on the medium-term effects of livestock ownership on nutrition outcomes.

A focus of this paper is the broader within-village effects of livestock donation programs. As livestock may produce more milk, meat, or labor than the household can use, programs providing livestock at the household level may have spillover effects on other households. This paper reviews the existing literature and compares results from three different estimation approaches to spillover effects: spatial, social, and program design. I attempt to disentangle effects due to village-specific markets for animal-source foods. The results provide empirical evidence for policymakers who are interested in maximizing the benefits of development interventions, as traditional measures that do not consider spillover effects may underestimate the total effect of the treatment.

I find evidence of direct and indirect treatment effects. For the households that received a dairy cow, livestock ownership results in an approximately 80% increase on average in the value of weekly per capita milk consumption. Households that participated in the Heifer International training program in the village that received dairy cows, but did not receive an animal by the end of the survey, saw an increase of about 15% on average in the per capita value of weekly milk consumption from gifts, an example of an indirect benefit from program design. The value of consumption from gifts also increased on average for households with dairy cow recipients in their social network, an example of a social spillover effect. Households that participated in the Heifer International training program in the village that received goats, but did not receive an animal by the end of the survey, saw an increase of about 45% on average in the per capita value of weekly meat consumption from gifts, an example of an indirect benefit from program design. I do not find evidence of spillovers along spatial networks. However, the allocation of network structure was not random or intentional, and thus the results across network structures and program designs must be interpreted cautiously.

2 Background

2.1 Livestock ownership

There are many pathways through which livestock ownership can lead to improvements in nutrition outcomes. The existing literature focuses on the direct impacts of livestock ownership; however there is limited evidence of the indirect effects of livestock ownership on other households. Animal source foods provide micro and macro nutrients as well as income from sales of livestock products such as milk, meat, manure, or draft labor (Whaley et al., 2003; Randolph et al., 2007; Headey et al., 2018). Livestock can increase access to market opportunities and serve as an investment vehicle for the household (Randolph et al., 2007; Nicholson et al., 2003). Livestock ownership may be associated with an increase in womens' bargaining power within the household based on gendered livestock management practices, which may lead to gender-based differences in food expenditure or consumption choices (Doss and Mcpeak, 2005; Kafle et al., 2018).

Rawlins et. al. (2014) used a similar Heifer International livestock donation program to study biometric outcomes for children in Rwanda, however their study was non-randomized, cross sectional only and relied on propensity score matching. The study found that livestock ownership increased dietary diversity for households that received dairy cows. Hoddinott et al. (2015) also used cross-sectional data and found ownership of a cow was associated with increased consumption of milk and decreased rates of stunting in rural Ethiopia. This study identified stronger effects on households in areas with limited local markets.

Two papers have been published based on the first four rounds of the same data used in this paper. Jodlowski et. al (hereafter ”Jodlowski”) (2016) found increases in total household expenditure for all treatment households and increases in probability weighted household dietary diversity for goat and dairy cow-recipient households. Kafle, et. al. (hereafter ”Kafle”) (2016) found similar increases in both food and nonfood expenditures and livestock revenues for all treatment households, with the largest increases for dairy cow recipients, and decreased subjective feelings of poverty by all treatment households. This paper will extend their analyses to include all eight rounds of data, to look beyond short-term impacts and consider the medium-term impact of livestock donation programs. In addition, I estimate social spillover effects by using a matrix of household participation in various social groups and spatial spillover effects using a measure of geographic proximity.

2.2 Estimation of Spillover Effects

The estimation of spillover effects in the economic literature has grown since 2000 and in general preceded estimation in the public health literature. Spillover effect estimation has been used for technology adoption, education, and food aid interventions. The approaches can be separated into general equilibrium effects, structural models of social or spatial learning, program design, and partial equilibrium effects along social or spatial dimensions. However, these approaches are not necessarily independent, and identification requires accounting for alternative explanations.

General equilibrium effects are the result of household and firm interactions affecting market prices and therefore equilibrium solutions. Heckman, Lochner, and Taber (1998) used an rational expectations, overlapping generations general equilibrium model to look at the effects of a tuition subsidy on school attainment and earnings. They show that the treatment effect framework is insufficient because the individuals who are affected are not just those who receive benefits, and the impact of the program on equilibrium skills prices and taxes is not captured by the framework. Because no true ”treatment-free” group can be identified, the differences-in-differences (DID) method of estimation will yield conservative estimates when spillover effects are present. This method requires data on market prices, quality, and participation.

The structural approach defines models where decision-makers update own beliefs after observing the actions and outcomes of other individuals within social or spatial networks. This method typically induces heterogeneity in information dispersion through various network structures in a controlled experiment. There is an extensive literature looking at spillover effects from technological adoption. Conley and Udry (2010) explored spillover effects from agricultural adoption to see how the benefits of a new technology move through social networks in Ghana using staggered adoption times and found evidence of social learning. Munshi (2004) demonstrated that information flows are weaker in heterogenous populations when the underlying characteristics are unknown, using data on wheat and rice growers during the Green Revolution in India . Chandrasekhar, Larreguy, and Xandri (2016) conducted experiments to test Bayesian and DeGroot learning models and found that agents were more likely to follow the DeGroot method of updating based on simple majorities. This literature focuses more on the determination of optimal network formation for information diffusion. Beaman et.al. (2018) design a field experiment with different models of entry points and diffusion strategies across social networks and find that the targeting strategy matters, and that spatial networks are a poor substitute for social networks. Chuang and Schecter (2015) provide an overview of the social network in developing countries and identify a gap in the literature in separating the mechanisms behind the network effects, such as the difference between the network's role in sharing information and its role in monitoring and enforcing monetary transfers.

Social and spatial spillovers have also been identified through program design. Miguel and Kremer's (2004) evaluation of a deworming program in Kenya used a step design of treatment delivery, allowing eligible groups that did not yet receive the treatment to serve as counterfactuals for the treatment group. Partial treatment within clusters yields unbiased estimates, but does not explain how the estimates vary with treatment intensity within a cluster (Moffitt et al., 2001). The economics literature has pointed out that randomization at the treatment level (or assignment to treatment level) does not guarantee that spillover effects are themselves random. Baird, et. al. (2016) recommend using a randomized saturation design where each cluster is assigned a treatment saturation and each individual within the cluster is randomly assigned a treatment status, given the assigned cluster saturation.

Partial equilibrium interaction effects occur when spillovers occur through social norms or geographic proximity, instead of through price effects. Manski (1993) termed social spillovers ”endogenous social effects.” He defined three types of effects: endogenous, exogenous (contextual), and correlated, where only the endogenous effects can lead to a multiplier effect. Bramouelle, et al (2009) improved upon Manski's model by relaxing the assumption of reference groups and defining a directed social network where the direction of influence is considered.

The tools for social spillover estimation are derived from spatial econometrics. Spatial models use geographic proximity to identify neighborhood effects (Anselin, 2001; Baltagi et al., 2003; Mutl and Pfaffermayr, 2010). Social spillover estimation evolved from this model by redefining the spatial weights using group membership or network participation (Kelejian and Prucha, 1998; Liu and Lee, 2010). Different weighting schemes are proposed to represent the intensity of influence of peers or neighbors (De Giorgi et al., 2010; fei Lee and Yu, 2010) while uncertainty can also be incorporated into the weighting matrix (Toulis and Kao, 2013).

Challenges persist for the econometric estimation of spillover effects. Angrist (2014) described some of the common challenges which have been addressed by the literature: leave-out means, overlapping peer groups, small group sizes, and he asserts that any residual peer effect is either the difference between the OLS and 2SLS results, or the result of a misspecified model. Guryan pointed out that even With random peer assignment and non-inclusion of the individual in his own group, there is necessarily a negative relationship between an individual's characteristics and the characteristics of his peers, as he is either above or below the peer average. This results in a downward bias in the OLS estimates of the peer effect, but can be corrected by including population averages of all potential peers (Guryan et al., 2009). Angrist offers a significantly simplified version of the Bramouelle model, and places it in a time series framework to show that the causal effects identified might actually be the result of misspecification in the error term. The spatial literature eschews OLS entirely and has focused on maximum likelihood estimation (MLE), two stage least squares (2SLS), or GMM. (Anselin, 2001) Thus skepticism is needed when developing models and interpreting the causality of results.

3 Data and Replication

3.1 Data

The Copperbelt Rural Livelihood Enhancement Support Project (CRLESP) is a HI-implemented project in five villages in the Copperbelt region of Zambia, with funding from Elanco Animal Health. HI projects require community groups to form and organize themselves in order to submit applications for assistance. Eligibility for donation is contingent on household participation in training activities, initial investments into facilities for animals in households, and contributions of 10 percent of the total cost of livestock received to a community insurance fund. Thus community groups that apply may be in villages that are relatively better off than other villages in the region, however these villages are similar in meeting the HI eligibility characteristics and self-selecting into the program. The selection of treatment and control villages among successful applicants was based on timing of application and availability of resources.

The program provided livestock to households in the form of dairy cows, draft cattle, and goats. The program was quasi-experimental where the distribution of livestock to households was staggered to create three full treatment groups (dairy cows, draft cattle, meat goats) of households that received livestock in year one termed "Originals," and three partial treatment groups of households that would receive subsequent generations of livestock termed "Pass on Gift" or "POG." One bull was given to each village that received draft or dairy cattle for reproductive purposes. POG households received training alongside original households at baseline. The community livestock group determined which households were Original and which were POG, although there is no discernable pattern in allocation. It is possible that POG households might change their behavior in anticipation of future livestock receipt. Jodlowski found no evidence of this behavior by looking at changes in expenditure for POG households in Rounds 1 and 2, prior to receipt of any animals.

Two eligible villages with community groups that applied but did not receive animals at any point during the program evaluation were termed "Prospectives." These villages are geographically separate from the treatment villages and were intended to receive livestock at a later date after the evaluation period. All households in the prospective villages are labeled "Prospective." Assuming there are no substantive differences between the treatment and prospective villages at the time of application, the prospective villages can serve as a control group following

De Janvry, et. al. (2010) Conditional on similarities between eligible villages, the staggered rollout eliminates the behavioral choice, there are no selection issues between adopters and non-adopters and a difference-in-differences model can be used. Treatment villages include households that did not participate in the farmers groups and did not receive treatment, termed ”Independents.” These households are likely different than households that selected into the program, and therefore are not used as a control group, but are used to provide general information about village trends.

In early 2012, Original households in Kamisenga received one pregnant dairy cow, households in Kaunga received two pregnant draft cattle, and households in Kanyenda received seven pregnant meat goats. The prospective communities were Chembe and Mwanaombe, which did not receive animals or training. The total livestock value transferred to each households was approximately 10,000 Kwacha, which is about 10 times the median asset level of a household. Data were collected in eight survey rounds between January/February 2012 and September/October 2017. Original treatment households were instructed to transfer subsequent generations of animals to POG households. Initially 324 households are surveyed and 291 remain by Round 8, an attrition rate of 10.2 percent. The balanced panel for the first four rounds used 300 households, the first six rounds used 275 households, and the balance panel for all eight rounds has 257 households.

Table 1: Sample Size and Attrition by Village and Treatment

	Round 1	Round 8	Difference	Attrition Rate
Chembe	31	29	-2	6.5%
Kamisenga	87	79	-8	9.2%
Kanyenda	115	101	-14	12.2%
Kaunga	55	52	-3	5.5%
Mwanaombe	36	30	-6	16.7%
Original	106	96	-10	9.4%
POG	111	101	-10	9.0%
Independent	40	35	-5	12.5%
Prospective	67	59	-8	11.9%
Total	324	291	-33	

As the assignment of treatment villages was not random, Table 2 presents the baseline characteristics of households during Round 1 to test the viability of the prospective communities as a control group. Baseline statistics for outcome variables are in Table 3. Note that the final column in both tables represents differences between independent and prospective households, and the independents are not intended to be a control group for any other group, but serve as a source of information about village-level trends. Variable descriptions are included in the appendix.

Treatment households were significantly larger than households in prospective villages at baseline. Original households cultivate significantly more land, and have more cattle and more goats than prospective villages. If this is true, then the decision to allocate treatment vs. prospective villages based on application timing may have been affected by the existing livestock knowledge and experience of villages who applied first, and thus the prospective villages may not be a reliable control group for the treatment villages. However, controlling for those characteristics in a difference-in-difference estimation will yield unbiased results.

3.2 Outcome Variables

Nutrition outcomes can be measured in terms of consumption levels, dietary diversity, or households' self-reported food security. I focus on the consumption of meat and milk products, disaggregated by three methods of acquisition: home production, purchases, and gifts. The outcome variable of interest is the log weekly per capita consumption value of milk or meat by acquisition method. Values are deflated to 2012 ZMK using inflation rates provided by the World Bank. While total expenditures are significantly different between Original and Prospective households, and POG and prospective households at baseline, none of the disaggregated milk and meat consumption values are significantly different for those pairs.

3.3 Replication and Extension

Two prior papers have been published from this data set which consider spillover effects. Jodlowski and Kafle both considered POG households as the recipients of potential spatial spillovers, based on the assumption that any animals received by the POG households were immature and unproductive. Both found increases in the value of milk consumption by POG households in the village that received dairy cows. While Jodlowski and Kafle assumed that POG households did not own productive animals through Round 4, it is unlikely that this is true through Round 8.

To account for this, POG households were reclassified in all specifications that utilized all eight rounds of data. For each round, if the POG household had received an animal from Heifer International during that round or in a previous round, it was labeled "POG_y," otherwise the household was a "POG_n." This designation will allow me to distinguish between social or spatial spillover effects on POG households without animals (POG_n), and treatment effects on POG households with animals (POG_y).

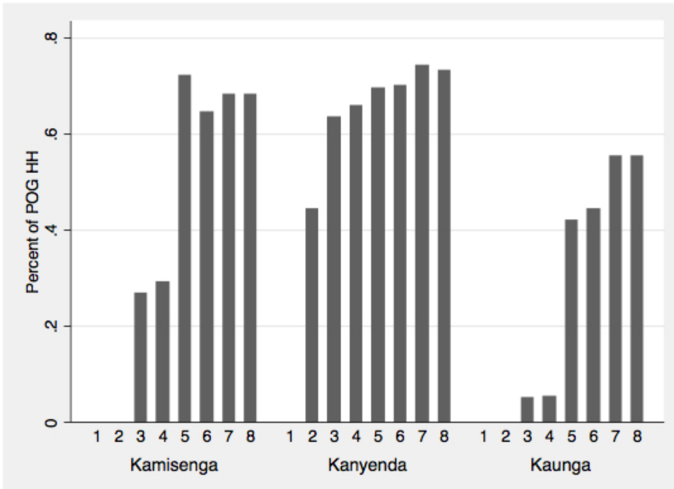


Figure 1: Percentage of POG households that have received animals by Round

I replicated the two papers and extended the authors' analyses through Round 8. A full explanation and results are included in Appendix B. After eight rounds, total expenditures increased by 35% for dairy cow recipients, 39% for draft cattle recipients and 43% for meat goat recipients, and 18% for POG households that received livestock. These effects were driven by increases in both food and non-food expenditures for all recipients. For draft households, the increase in nonfood expenditure is more than three times that of food expenditure, supporting the hypothesis that those households are not shifting wealth increases into consumption.

After Round 8, the value of milk consumption per capita increased by about 80% for dairy cow households and 40% for POG recipient households. This effect is smaller than the effects seen after Round 4 for treatment households, which may be due to aging of animals. Meat consumption per capita increased by 50% for dairy cow households, 100% by meat goat households, and about 60% for POG recipient and non-recipient households. This effect was similar to the effect seen after Round 4. Livestock revenue increased by over 400% for dairy cow households and 95% by draft cattle households, but there were no significant increases for meat goat households. These effects were consistent and persistent from Round 4 to Round 8. Based on the increase in meat consumption by meat goat households, it seems likely that those households chose to consume rather than sell their goats, while the dairy cow households were able to increase both consumption of milk and livestock revenue simultaneously.

Table 2: Baseline characteristics by treatment

	Original	POG	Independent	Prospective	Orig v.Pros	POG v.Pros	Indp v.Pros
Household size	7.406	6.919	5.975	5.731	-1.674***	-1.188**	-0.244
	(2.801)	(2.754)	(2.370)	(2.157)			
Number of kids under 5	1.179	1.270	1.125	1.015	-0.164	-0.255	-0.110
	(1.003)	(0.943)	(1.042)	(0.913)			
Number of kids 6-16	2.396	2.450	2.025	1.776	-0.620**	-0.674**	-0.249
	(1.631)	(1.741)	(1.441)	(1.391)			
Dependency ratio	0.462	0.521	0.483	0.446	-0.016	-0.075*	-0.037
	(0.204)	(0.174)	(0.212)	(0.217)			
Household Head Characteristics							
Education Level	2.509	2.523	2.225	2.687	0.177	0.164	0.462*
	(1.205)	(1.285)	(1.165)	(1.047)			
Gender (1=Female,0=Male)	0.283	0.252	0.325	0.209	-0.074	-0.043	-0.116
	(0.453)	(0.436)	(0.474)	(0.410)			
Marital Status (1=Yes, 0=No)	0.821	0.874	0.825	0.791	-0.030	-0.083	-0.0340
	(0.385)	(0.333)	(0.385)	(0.410)			
Household Assets							
HH durable assets 2012 ZMK	2071.2	1759.3	749.8	1302.5	-768.7	-456.8	552.7**
	(3982.0)	(3885.4)	(630.0)	(1241.4)			
HH durable assets 2012 USD	828.7	703.9	300.0	521.2	-307.6	-182.8	221.2**
	(1593.3)	(1554.6)	(252.1)	(496.7)			
Total Land	3.098	2.843	0.969	2.002	-1.096*	-0.841*	1.034***
	(4.939)	(3.145)	(0.925)	(1.409)			
HH herdsize in TLU	1.377	0.741	0.262	1.233	-0.145	0.491	0.971**
	(1.893)	(1.797)	(0.489)	(2.595)			
Number of cattle	1.208	0.550	0.0250	0.776	-0.431	0.227	0.751**
	(2.211)	(2.177)	(0.158)	(2.058)			
Number of goats	2.500	1.505	0.225	1.224	-1.276*	-0.281	0.999**
	(4.870)	(3.272)	(0.920)	(2.315)			
TV ownership (1=Yes, 0=No)	0.472	0.387	0.100	0.388	-0.084	0.001	0.288***
	(0.502)	(0.489)	(0.304)	(0.491)			
Bicycle ownership (1=Yes,0=No)	0.840	0.820	0.700	0.866	0.026	0.046	0.166
	(0.369)	(0.386)	(0.464)	(0.344)			
Observations	106	111	40	67			

Point estimates are mean; Standard deviations are in parentheses; the last three columns contain the difference between group means and their significance

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Outcome Variables at Baseline by Treatment Type

	Original	POG	Independent	Prospective	Orig v. Pros	POG v. Pros	Indp v. Pros
Total expenditures	31.17	33.90	28.39	45.04	13.87**	11.14*	16.65***
(weekly per capita 2012 ZMK)	(19.10)	(28.16)	(18.35)	(30.89)			
Total expenditures	12.47	13.56	11.36	18.02	5.55**	4.46*	6.66***
(weekly per capita 2012 PPP USD)	(7.64)	(11.27)	(7.34)	(12.36)			
Food share as % of expenditure	0.546	0.560	0.619	0.543	-0.003	-0.018	-0.076*
	(0.167)	(0.188)	(0.178)	(0.169)			
ASF share as % of expenditure	0.139	0.142	0.177	0.157	0.018	0.015	-0.020
	(0.121)	(0.118)	(0.157)	(0.119)			
Livestock revenue	2.809	3.932	1.126	8.378	5.569	4.446	7.252*
(weekly per capita 2012 ZMK)	(8.365)	(10.86)	(2.530)	(26.49)			
Milk consumption days	1.283	1.126	0.725	1.716	0.433	0.590	0.991*
(per week)	(2.097)	(2.068)	(1.536)	(2.707)			
Meat consumption days	1.009	1.216	0.775	1.209	0.200	-0.007	0.434*
(per week)	(0.941)	(1.404)	(0.832)	(1.274)			
Milk consumption from purchases	0.592	0.399	0.559	0.511	-0.081	0.112	-0.048
(weekly per capita 2012 ZMK)	(1.097)	(1.045)	(1.277)	(1.338)			
Milk consumption from production	0.016	0.035	0	0.132	0.116	0.097	0.132*
(weekly per capita 2012 ZMK)	(0.089)	(0.158)	(0)	(0.509)			
Milk consumption from gifts	0.028	0.037	0	0.021	-0.008	-0.017	0.021
(weekly per capita 2012 ZMK)	(0.199)	(0.210)	(0)	(0.101)			
Meat consumption from purchases	2.309	2.371	3.007	3.703	1.395	1.332	0.696
(weekly per capita 2012 ZMK)	(3.389)	(4.067)	(4.681)	(5.583)			
Meat consumption from production	1.079	2.309	0.879	2.189	1.110	-0.121	1.310
(weekly per capita 2012 ZMK)	(3.155)	(9.130)	(2.693)	(4.375)			
Meat consumption from gifts	0.149	0	0.320	0.083	-0.065	0.083	-0.237
(weekly per capita 2012 ZMK)	(1.061)	(0)	(1.362)	(0.677)			
Observations	106	111	40	67			

Point estimates are mean; Standard deviations are in parentheses; the last three columns contain the difference between group means and their significance

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Conceptual Framework

The decision by the household to produce or purchase a good is affected by the functionality of the market for that good. If there are significant transaction costs to participating in formal markets, or if those markets do not exist, households may choose to gift or trade goods informally with neighbors or friends. As meat and milk products are both perishable, participation in formal markets requires storage capacity and reliable and frequent access to those markets. Households facing complete markets will make consumption choices separately from production choices, but those facing incomplete markets due to high transaction costs will jointly make those decisions. Households may be more likely to trade meat and milk informally than less perishable goods produced by the household. This decision can be viewed through the conceptual framework of agricultural household separability.

The Singh, Squire and Strauss (1986) model specifies the utility maximization problem for an agricultural household under complete markets. The utility maximizing household will seek to optimize:

$$U = U(X_c, X_m, X_l) \tag{1}$$

for X_c=agricultural good, X_m=goods only purchased in the market, X_l=leisure. The welfare function is twice differentiable; first derivatives are positive with respect to all argument. It is subject to a cash constraint:

$$p_m X_m = p_c(Q - X_C) - w(L - F) \tag{2}$$

Where L =all labor provided by the household and hired labor, Q = household production of C, and F = total labor supplied by the family on and off farm. The prices of the market good (p_m), agricultural good (p_c), and the wage (w) are exogenous and determined by the market. Non-labor and non-farm income is assumed to be zero. It is subject to the production constraint and time constraint:

$$Q = Q(L, A) \qquad X_l + F = T \tag{3}$$

where A = all other inputs other than labor, including land and T = total time for the household. Combining the constraints yields the Full Income Budget Constraint:

$$p_m X_m + p_c X_c + w X_l = wT + p_c Q - wL = Y^* \tag{4}$$

Under separability of production and consumption choices, L^* is a function of prices, production capability, and other inputs. The right hand side of equation (4) can be replaced by Y^*, the income derived by a profit-maximizing household. The maximization of utility subject to this constraint yields demand functions of the form:

$$X_j^*(p_m, p_c, w, Y^*) \qquad \text{where } \ j = m, c, l \tag{5}$$

However, markets may be incomplete due to inability to hire outside labor, or for household members to work off farm, or due to transaction costs for bringing the good to market, such as perishability or distance to market. There may also be limitations on the types of goods that are available in the market, yielding non-exogenous ”shadow” prices for non-marketable goods. Thus the separability assumption fails and consumption decisions are functions of production inputs as well:

$$X_j^*(p_m, p_c, w, Y^*, L^*, A^*) \qquad \text{where } \ j = m, c, l \tag{6}$$

The Heifer International program provided treatment households with three types of livestock: dairy cows, meat goats, and draft cattle. The transfers were normalized to represent the same income shock: one dairy cattle = seven meat goats = two draft cattle. Each transfer represents an income shock to the full income budget constraint: dairy cows provide milk (increase in M), meat goats provide meat and milk (increase in M), and draft cattle provide labor and milk (increase in M and F.) Therefore under the assumption of complete markets, the effect of these transfers on household consumption and labor choices is identifiable. It is likely that separability fails for households in this context due to limited storage capacity or reliable and frequent access to milk or meat markets.

Under incomplete markets, household agricultural production may be the primary source of nutrition for the household. If food items cannot be reliably purchased from the market, agricultural households may choose to optimize production based on nutritional goals, instead of solely on profit maximization (Hoddinott et al., 2015). Infrastructure limitations, information assymmetries, and limited marketing systems can results in price uncertainty that encourages agricultural households to prioritize self-sufficiency over profitability (de Janvry et al., 1991). In this context, households may choose to trade informally to maximize profits if there are transaction costs or price uncertainty in formal markets. Households may also share with other households as a form of consumption smoothing or consistent with a social norm as a participant in the Heifer International program.

5 Peer Effects Methodology

As milk and meat are perishable items, it is likely that households would prefer to sell or gift any production in excess of household consumption in lieu of storage. These transfers, via formal markets or informal channels, represent indirect benefits to non-recipient households in the form of increases in consumption. There are various pathways through which indirect effects may result from livestock ownership.

This paper focuses on four:

- Program Design Effects: ”Pass on Gift” (POG) households were required to attend Heifer training alongside Original households. In addition, there was a staggered distribution of second generation livestock to POG households in arbitrary order. If treated households have excess meat or milk, they may prioritize sharing with other households that are participating in the Heifer program as a form of consumption smoothing. Original and (POG_y) households might prioritize sharing with POG households that have not yet received animals (POG_n) to compensate those households for not yet receiving an animal. For POG_y households, the direct program effect would be increased consumption from home production, while the indirect program effect would be increased consumption from gifts.
- Social Spillovers: Households may share information or goods with other households participating in defined social groups. In rural areas such as the CRLESP setting, informal good sharing might occur as a result of limited market access or availability and the perishability of milk and meat products. Information sharing would occur if treatment households that participate in a Heifer-led training program on livestock ownership choose to share this information with households in their social network, resulting in changes in livestock practices or consumption of animal source foods.
- Spatial Spillovers: Akin to social effects, households may share information or goods with geographically proximate households that may or may not be in their social networks.
- Price Effects: The increase in supply of animal-source foods brought to village markets may lead to lower market prices resulting in increased average consumption of animal source foods in the village. However, lower market prices combined with transaction costs in bringing meat or milk to formal markets might encourage households to trade with each other rather than incur those costs. Additionally the increase in purchasing power by recipient households might drive up prices in those villages if supply does not expand accordingly.

Disentangling these pathways can support the identification of the optimal village network structure for maximizing the direct and indirect benefits of livestock transfer programs. However without an intervention design that tests spatial structure, social network structure, and program design simultaneously, it is not possible to identify which pathway maximizes program benefits.

If spillovers occur through social networks or through specific network structures, then villages with robust social networks might see larger benefits than weakly networked villages or from targeting strategies that are not network-specific. If sharing occurs due to spatial proximity, then villages with tightly clustered households may benefit more than villages with dispersed households. Finally, if spillovers are concentrated within POG households who did not receive any animals (POG_n), then program benefits be maximized under a design which designates additional households as POG, but does not necessarily provide those households with animals. The benefits from the first three pathways are cost-free. The inclusion of additional households in training programs has a minimal cost, but is substantially less than the cost of providing livestock. The village selection strategy did not consider network structure, and the household sampling was not designed to capture sufficient non-recipient households to determine which network structure maximizes benefits. However, the results from these estimations may provide evidence to support future research to fully identify relative spillover effects.

5.1 Spatial Spillovers

5.1.1 Methodology

Spatial econometrics provides the tools for estimating spatial spillovers. Initially spatial econometrics focused on two separate approaches: spatial autocorrelation models and modelling spatial heterogeneity (Anselin, 2001). The former approach specifies a model which includes a spatially lagged version of the dependent variable. The latter is used when spatial autocorrelation is present, but tests do not indicate that the inclusion of a spatial lag in the model would be useful, and thus the spatial component of the error term must be addressed through other econometric means. These approaches were combined into SARAR models that incorporate both spatial lags and spatially autocorrelated errors (Kelejian and Prucha, 1998; Baltagi et al., 2003). There is also support for Spatial Durbin models that incorporate lags of explanatory variables (Paul Elhorst, 2014). Spatial panel models extend these approaches to an additional dimension and allow for spatial and serial correlation (fei Lee and Yu, 2010; Kapoor et al., 2007; Baylis et al., 2011). Estimation of spatial panel models is implemented either by maximum likelihood (ML) or generalized method of moments (GMM) (fei Lee and Yu, 2010; Kelejian and Prucha, 1998; Kapoor et al., 2007). Both approaches require restrictions on the spatial weighting matrix, and on the distribution of the outcome variable to produce consistent and asymptotically efficient estimators.

While the most common specification test for spatial autocorrelation with cross-sectional data is the Moran test, this statistic is insufficient for spatial panel models. When ML is used, inference is based on a likelihood ratio test if an alternative model is estimable or a Lagrange Multiplier (LM) test is used. Baltagi, Song, and Koh (2003) developed several LM tests for panel data regression models with spatial and serial error correlation.

If households with excess goods or program information are sharing with geographically proximate households, then the mechanism for the spillover is program participation and a spatial lag on treatment is most appropriate. If there is correlation between proximate households due to other unobservable factors, that would manifest in a spatially lagged error. This model is defined as a Spatial Durbin Error Model that includes lagged covariates and an autoregressive error (**?**).

$$Y = X\beta + (I_T \otimes G_N)X\theta + (I_T \otimes W_N)X\gamma + (\iota_N \otimes I_T)\alpha + u \tag{7}$$

where y is an NTx1 matrix of observations of the dependent variable, X is a NTxk matrix of finite exogenous regressors including dummies for treatment categories, I_T is an identity matrix of dimension T, G_N (W_N) is an NxN spatial (social) weighting matrix, ι_N is a Nx1 vector of ones,I_T is an identity matrix of dimension T, α is a Tx1 matrix, and θ (γ) is the spatial (social) parameter of interest for the exogenous variables. Both the household effect and the disturbances can be spatially correlated (Kapoor et al., 2007). The disturbances can thus be decomposed:

$$u = \rho(I_T \otimes M_N)u + \varepsilon \tag{8}$$

where M_N is an NxN matrix of spatial weights, which may be equivalent to G_N or W_N. The spatial or social parameter of interest for the disturbances is ρ and ε are innovations correlated over time and households:

$$\varepsilon = (\iota_T \otimes I_N)\mu + \nu \tag{9}$$

where ι_T is a Tx1 vector of ones,I_N is an identity matrix of dimension N μ is Nx1 a vector of time-invariant household effects, and ν are assumed to be independent and identically distributed over households and time with mean zero and variance σ_ν^2 with finite absolute $4+\psi_\nu$ moments for some $\psi_\nu > 0$ T and N are fixed.

The spatial weights in W and M are assumed to be identical and non-stochastic. Formally, W is a row-normalized positive NxN matrix with elements $w_{ij} = \frac{1/d_{ij}}{\sum_j \frac{1}{d_{ij}}}, i = 1,...,N ford_{ij} < 25km$ where d_{ij} is the euclidean distance between household$_i$ and household$_j$ for $j = 1,..,N$ households, with $w_{ii} = 0$. Thus matrix $(I_N - \rho W_N)$ is non-singular and uniformly bounded in absolute value. Row-normalization yields a weight that is interpreted as the fraction of all spatial influence on household$_i$ that can be attributed to household$_j$. It does however have other effects, most notably when a lagged dependent variable is included.

In the fixed effects panel model, the incidental parameter problem prevents identification of the fixed effects. The within transformation using deviations from the time mean would result in linear dependence over time in the ν term. Thus Lee and Yu (2010) utilize a transformation based on the orthonormal eigenvector matrix of the time mean operator. This transformation does not induce serial correlation in the errors, but does require that the weighting matrix be row normalized. For short T, the time effects are estimated as additional regression coefficients and only one transformation is performed.

Formally, equation (8) is pre-multiplied by the TxT matrix J

$$\text{where } J = \begin{pmatrix} \sqrt{\frac{T-1}{T}} & \frac{-1}{\sqrt{T(T-1)}} & \frac{-1}{\sqrt{T(T-1)}} & \cdots & \frac{-1}{\sqrt{T(T-1)}} & \frac{-1}{\sqrt{T(T-1)}} \\ 0 & \sqrt{\frac{T-2}{T-1}} & \frac{-1}{\sqrt{(T-1)(T-2)}} & \cdots & \frac{-1}{\sqrt{(T-1)(T-2)}} & \frac{-1}{\sqrt{(T-1)(T-2)}} \\ 0 & 0 & \sqrt{\frac{T-3}{T-2}} & \cdots & \frac{-1}{\sqrt{(T-2)(T-3)}} & \frac{-1}{\sqrt{(T-2)(T-3)}} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{\frac{1}{2}} & -\sqrt{\frac{1}{2}} \end{pmatrix}$$

This transformation yields:

$$Y_{nt}^* = X_{nt}^*\beta + \theta G_n X_{nt}^* + \gamma W_n X_{nt}^* + \rho M_n U_{nt}^* + \alpha_{nt}^* \iota_n + V_{nt}^* \text{ , for } t = 1 \ldots T-1 \tag{10}$$

For i.i.d. $v_i t$, $E(V_{n1}^{*'} \ldots V_{n,T-1}^{*'})'(V_{n1}^{*'} \ldots V_{n,T-1}^{*'}) = \sigma_v^2 I_{n(t-1)}$ and thus the $v_{it}^{*}{}'s$ are uncorrelated for all i and t and independent under normality. The resulting likelihood function is conditional based on time averages $\bar{Y_{nT}}$, which are a sufficient statistic for the time-invariant household effect under the assumption of normality of the original residuals. Let $Z = [X\ WX\ GX]$ $\delta = [\beta\ \theta\ \gamma]$. K is the number of parameters in β which is equal to the number of parameters in θ and in γ. Then the log likelihood function for normally distributed disturbances is:

$$ln L_{n,T}(\delta, \rho, \sigma^2|y) = \frac{-n(T-1)-2k}{2} ln(2\pi\sigma_v^2) + (T-1)[ln|I_n - \rho W_n|] - \frac{1}{2\sigma_v^2}\sum_{t=1}^{T-1} V_{nt}^{*'}(\delta)V_{nt}^*(\delta) \tag{11}$$

The estimation procedure iterates between the reduced likelihood function and Generalized Least Squares (GLS) until convergence: estimates of the residuals of the transformed model are used to estimate ρ, which is then used to estimate β, θ,γ, and σ_v as feasible GLS estimators. The parameters of the household fixed effect terms are not identified under this approach. Any spatial correlation in the household effect is also not identified under any fixed effect transformation. This approach is chosen over a method of moments approach because of multicollinearity between the lagged covariates and the instruments, and because it eliminates AR(1) serial correlation in the errors.

The QMLEs of δ and σ^2 given ρ are:

$$\hat{\delta}_{nT}(\rho) = \left[\sum_{t=1}^{T} \tilde{Z}_{nt}'(I_n - \rho W_n)'(I_n - \rho W_n)\tilde{Z}_{nt}\right]^{-1} \times \left[\sum_{t=1}^{T} \tilde{Z}_{nt}'(I_n - \rho W_n)'(I_n - \rho W_n)\tilde{Y}_{nt}\right] \tag{12}$$

$$\hat{\sigma^2_{nT}}(\rho) = \frac{1}{n(T-1)} \sum_{t=1}^{T} \left[\tilde{Y}_{nt} - \tilde{Z}_{nt}\hat{\delta}_{nT}'(\rho)\right]' \times \left[(I_n - \rho W_n)'(I_n - \rho W_n)\right] \left[\tilde{Y}_{nt} - \tilde{Z}_{nt}\hat{\delta}_{nT}'(\rho)\right] \tag{13}$$

where $\tilde{Z}$ are from estimation of equation (11). Substituting back in to equation 12 yields the concentrated likelihood function:

$$\mathrm{lnL}_{n,T}(\rho|y) = \tfrac{-n(T-1)-2k}{2} ln((2\pi)+1) - \tfrac{n(T-1)-2k}{2} ln\hat{\sigma^2_{nT}}(\rho) + (T-1)ln|I_n - \rho W_n| \tag{14}$$

This is the concentrated likelihood function that will use for the spatial spillover analysis.

5.2 Social Spillovers

5.2.1 Methodology

If households who have received animals (Original and POG_y) produce more milk or meat than can be consumed by the household, or more draft labor than the household needs for itself, it is possible that the household might share with other households in their social networks. A social network could be the set of all household-to-household connections in a village, or the set of all memberships in defined social groups within a village.

The preliminary peer effects model provided by Manski (1993) distinguished between three types of peer effects: *exogenous*, which is the effect from the characteristics of peers, *endogenous*, which is the effect from the outcomes of peers, and *correlated*, which are common shocks to peers. This is referred to as the ”linear-in-means” model, further clarified by Bramouelle and DeGiorgi (Bramoullé et al., 2009; De Giorgi et al., 2010).

$$y_i = \alpha + \beta E(y|G_i) + \gamma E(\mathbf{x}|G_i) + \delta x_i + u_i \tag{15}$$

where y_i is the outcome for household i, G_i is the reference group for household i, x_i are characteristics of household i, u_i is composed of the household fixed effect μ_i, group fixed effect θ_g, and a noise component ε_i

The coefficient β captures the endogenous effect of the household outcome y varying with the mean outcome of the households$_{j\neq i}$ in the reference group G_i. The coefficient γ captures the exogenous effect of the household outcome varying with the mean of the exogenous variables x of other households$_{j\neq i}$ in the reference group G_i. The coefficient δ reflects the correlated effects that are from the household outcome being correlated with other households that have similar characteristics x.

There are two main identification issues: the endogeneity problem and the reflection problem. The endogeneity problem results from selection into groups by households and from common shocks that affect each group. Therefore any correlation between the household outcome and group outcome may be due to correlated effects or endogenous group formation, instead of a true peer effect. Thus the endogenous and exogenous effects cannot be differentiated from the correlated effects. $Cov(\mu_i, E(y|G_i)) \neq 0$ or $Cov(\mu_i, E(\mathbf{x}|G_i) \neq 0$

The reflection problem is that even if it is possible to distinguish endogenous and exogenous effects from correlated effects, or if there are no correlated effects, there is a simultaneity issue that leads to perfect collinearity between the mean outcome of the group and its mean characteristic, making it difficult to distinguish between the endogenous and exogenous effects. $Cov(\theta_g, E(y|G_i)) \neq 0$

Bramouelle, et al improved upon Manski's model by relaxing the assumption of reference groups and defining a directed social network where the direction of influence is considered. This transformation can be accomplished in two ways: locally by modeling the deviation from the mean of the household's neighbors, and globally by modelling the deviation from the household's network. Bramouelle uses network fixed effects to control for correlated effects and eliminated the household of interest is excluded from all mean calculations. Under this assumption, it is possible to separate the endogenous and exogenous effects.

DeGiorgi uses a similar approach to eliminate the reflection problem using individual-specific reference groups. If household$_i$ belongs to groups a, b, c and household$_j$ belongs to groups b, c, d, then the mean outcome for household$_i$ is no longer equivalent to household$_j$ and identification is achievable. The endogeneity problem could be resolved with random assignment to treatment groups, which would eliminate endogenous selection into treatment or correlated effects, however this would certainly maintain the reflection problem because treatment groups would no longer be household specific. Thus the solution suggested by DeGiorgi is to use groups defined by characteristics other than treatment assignment, such as social groups or classes, and resolve the endogeneity issue using an instrumental variables (IV) approach, which uses the characteristics of excluded households to separate the endogenous and exogenous effects from the correlated effects. The characteristics of household$_k$, which is in household$_j$'s reference group but is not connected to household$_i$, will affect household$_i$ through their effect on household$_j$, however household$_k$ will not be subjected to the same shocks as the households in household$_i$'s reference group. The exclusion restriction is satisfied because x_k affect y_i only through y_j. The square of matrix G represents the second degree connections between households and is part of the instrumental variable as defined. Assuming that there is not perfect overlapping in group membership, then G and G^2 will be linearly independent, abrogating the reflection problem and allowing for identification of equation (13). This structure is not feasible in a spatial framework using inverse distances, because household$_k$ would affect household$_i$, given that $d_ik < \bar{d}$.

While others used a G matrix that only considered the binary existence of other peers in individual i's peer group, DeGiorgi adjusted this matrix to consider the strength of peer contribution, weighting each student$_j$ by the number of classes student$_j$ took with student$_i$.The random allocation of peer groups eliminated correlation between the individual effect and any endogenous or exogenous effects, and thus the IV was used to address endogeneity due to correlated groups shocks. For the CRLESP program, group participation is endogenous, and thus all three social effects cannot be identified. If sharing of extra goods or program information is along social pathways, then including lagged treatment variables is most appropriate. Any spillovers due to unobservable factors effecting households in the same social groups would be capture by an autocorrelated error term. Thus a Durbin Error model is the most appropriate model for testing social spillover effects, substituting a measure of social closeness for spatial proximity to define the weighting matrix W.

5.2.2 Social Network Data

For the CRLESP project, data was collected on group membership during Round 8, presented in Table C.1 in the Appendix. The 13 types of groups are those included in the G4 module of the Women's Empowerment in Agricultural Index (WEAI) survey conducted by the International Food Policy Research Institute (IFPRI) (Alkire et al., 2013).

Enumerators were instructed to inform the respondent that the definition of the group could be formal or informal. Thus the instrument is not capturing "official" group participation, as there was no proof required of group existence or membership. Instead, the survey instrument captures the respondent's belief that someone in the household participates in a certain type of social group. Therefore measurement error could occur through both underreporting of participation by influential individuals, or by overreporting of individuals who are not truly being influenced by peers. It is unclear which error is more likely, and thus the interpretation of results is that the influence lies with a belief in group participation instead of actual participation.

The groups with the highest percentage of participation are livestock, crop, government, civic, religious, and womens. (Appendix Table C.1) The strongest correlations are between livestock and crop groups, water and fishing groups, trade and insurance groups, mens and civic groups, and women and religious groups. (Table available upon request) Villages are spatially distinct, and are assumed to be socially distinct as transportation is primarily on foot.

For the CRLESP project, the contribution of household$_j$ is weighted by the relative number of groups it has in common with household$_i$ for ij within the same village. Once again, it is assumed that the weighting structure for the lagged covariates and lagged error is the same. Formally, W is a row normalized weighting matrix constructed with $w_{ijv} = \frac{p_{ijv}}{\sum_j p_{ijv}}$ where p_{ijv} is the total number of connections between household$_i$ and household$_{j \neq i}$ within village$_v$ where $v \in [1,5]$. $p_{ijv} = r$ if household$_{j \neq i}$ belongs to r groups of the 13 possible groups that household$_i$ belongs to for $r \in [0,13]$. p_{ijv} =0 if household$_i$ and household$_j$ do not belong to the same village$_v$. Thus the matrix $(I_N - \rho W_N)$ is non-singular. The interpretation of the social parameter is similar to that of the spatial parameter in capturing the fraction of influence household$_j$ has on household$_i$.

The network graphs are included in Figure C.1 in the Appendix. All centrality measures are graph-level scores based on the node-level values normalized by the theoretical maximum for a graph with the identical number of vertices. There are many isolated households in all five villages. Kamisenga represents the most closely networked village, where closeness centrality measures how many steps are required to access every other vertex from a given vertex, and on degree, which measures the number of adjacent edges of the vertices. Both closeness centrality and degree centrality reward villages with a few highly influential households that have many social connections. Chembe scores highest on betweeness which is the number of shortest paths between nodes that pass through each vertice. Betweenness centrality prioritizes the capacity to spread information quickly around a village. Chembe also has the largest diameter however, which is the length of the longest path between any two vertices. This can be seen in the network graph Figure C.1(a) as the two isolated households that have very few direct connections.

5.3 Price Effects

A general equilibrium (GE) model is required to determine whether consumption changes are due to market effects. However, this requires extensive data and fully functioning markets, which is unlikely to be true of the villages participating in the CRLESP program. It is instructive however to look at the spatial-temporal changes to understand the structure of local markets.

In Figures D.1 and D.2 in the Appendix, the mean per capita weekly milk and meat consumption values are disaggregated into purchases, production, and gifts by round and by village. The solid lines represent the median prices derived by round and village from reported purchase values and quantities. Total value and prices are normalized to 2012 ZMK. The dotted lines represent the expected price of the good that is used in the calculation of production value and gift value from reported production and gift quantities. Further information about these variables is included in the appendix.

Figure D.1 shows milk price spikes in Chembe and Kaunga in Round 7, and fluctuations in Kanyenda that do not appear to correlate with decreases in purchases. This may be because of poorly functioning markets without complete price transmission. In Figure D.2, price spikes occur in all villages in Round 7. There are also meat price spikes in Rounds 2-7 in Kamisenga, where households received dairy cows. If dairy cow ownership increases household income, recipient households might demand more meat, resulting in a higher market price. There was high inflation in Zambia in 2016 when survey Rounds 5 and 6 occurred.

In order to test the behavior of prices within villages I regressed the nominal derived prices on village, round, village*round interaction, and the number of treated in each village. These results are included in Table D.1 in the Appendix. There is ample evidence of village-specific time trends affecting meat prices in all rounds, and some evidence of trends for milk, however the source of these trends are unclear. The large positive coefficient on the number of treated individuals in Kamisenga may be the result of increased demand for meat due to increased dairy cow income for treatment households, with no accompanying supply expansion to meet the demand shift. This hypothesis is also supported by the significant coefficients on the Round*Kamisenga interactions in Rounds 3,5, and 7, which were surveys held during the rainy season when dairy cows are more productive.

A potential strategy to isolate price effects is to compare disaggregated consumption streams. Households can acquire animal source foods as gifts from other households, or purchase items from households or local markets. If the program increases the quantity and decreases the price of meat or meat available in the market, then it is more likely that meat and milk purchases would increase. If spillovers occur through social or spatial mechanisms and not through market effects, it is more likely that meat and milk gifts would increase. While the Round 8 survey asked for the location of milk purchases, prior rounds did not. Therefore these two pathways are not able to be identified with this data set. While estimating the consumption streams separately might help understand sharing mechanisms, this strategy will not definitively identify price effects.

6 Empirical Results

If sharing is due to surplus production of meat or milk and there are transaction costs to participating in formal markets, it is likely that proximate or networked households would exhibit increased total consumption due to informal purchases or gifts. If it is information being shared, it is likely that proximate or networked households would increase total consumption due to market purchases or home production. As there is only data on location of purchases for

Round 8, it is not possible to identify the two distinct types of purchases. Thus the outcomes of interest are milk consumption from gifts and home production, after controlling for geographic factors correlated with production with the spatially autocorrelated error term. I estimate Spatial and Social Durbin Error models ($\rho = \theta > 0$) and Spatial and Social Error models. These were compared to the Fixed Effects specification and the best model was selected for each outcome based on significance, AIC, and BIC tests.

6.1 Discussion

The results of the spillover effect estimation for milk consumption are presented in Table 4. For each outcome variable: total consumption, consumption from gifts, consumption from purchase, and consumption from production, the top model was selected and is included. Column 1 represents the base model with household fixed effects for aggregate consumption value. This specification is analogous to model K1 in the replication Table 4, with the separation of POG households by livestock type. For original dairy cow recipients, the 81% increase in total consumption can be attributed to increased production and decreased purchases.

For milk consumption, none of the spatial models provided any information over the base fixed effect model. Thus there is no evidence that spatial proximity is the preferred pathway for milk sharing. There is evidence of milk gifts along social connections in Kamisenga, the dairy village. Households that were connected to POG_Dairy_y recipients saw over a 200% increase on average in the value of milk gift consumption value per capita per week. There is evidence that program designation is significant based on gifting to POG non-recipient in the dairy village. POG_Dairy_n recipients experienced a 15% increase in milk gift consumption value per capita per week. There is evidence that market effects may have led to increased consumption of milk by POG_n. This could be due to lower meat prices allowing for a larger part of the household budget to shift to purchasing of milk.

The results of the spillover effects estimation for meat consumption are presented in Table 5. For each outcome variable: total consumption, consumption from gifts, consumption from purchase, and consumption from production, the top model was selected and is included. For original goat recipients, the 125% increase in total weekly meat consumption value per capita can be attributed to increased production, purchases, and gifts.

The spatial error model was selected for total expenditure and gift consumption. There was no evidence of spatial spillovers for purchases or production. The social error model was selected for total expenditure and gift consumption. There was no evidence of social spillovers for purchases or production. There is evidence that program designation is significant based on gifting to POG non-recipient in the goat village. POG_Goat_n recipients experienced a 45% increase in meat gifts after accounting for social and spatial correlation in unobservable effects. There were increases in meat purchases in all treatment villages. It is uncertain if the increased meat consumption values by Original, POG_y, and POG_n households in the dairy cow village are due to higher prices from increased demand, or if the larger meat consumption values are themselves a function of the higher prices.

7 Conclusion

I find evidence of direct treatment effects and indirect effects from social networks and program design. The lack of empirical results on social and spatial spillovers should not necessarily be perceived as a failure, but as an incentive to design programs to more accurately capture spillovers. The identification of spillover effects is difficult both empirically and econometrically. The lack of consensus on econometric estimation of peer effects is a major impediment to identification. Empirical estimation is hindered by survey design and measurement error. Papers that have been successful in identification of spillovers have incorporated network effects into the planning of the program, and used more sophisticated techniques in network mapping, such as photo identification of networked individuals.

The importance of the identification of spillover effects drives the continued search for solutions to the current measurement and specification issues. Both the quantity and type of livestock provided to households is calibrated by the type of village. Thus it is important to quantify spillover effects among possible pathways: through program design, through social networks, or due to spatial proximity. If households share excess milk, meat, or labor along social connections, then development organizations could maximize program effects by selecting villages with large existing social networks. If households share along spatial connections, then development organizations could maximize program effects by selecting villages where houses are more closely located. If there are effects on POG-non recipient households, then development organizations could increase program effects by increasing the number of POG-defined households, even if those households will not receive animals. The identification of spillover effects, analysis of spillover pathways, and subsequent program management could be important tools in addressing nutritional deficits in rural Africa.

Table 4: Spillover Effect Estimation: Milk Consumption Value

After X Dairy	0.624***	0.829***	0.005	-0.21**
After X Goat	0.293**	0.342***	0.025	-0.087
After X Draft	0.453***	0.511***	-0.018	-0.034
After X POG_Dairy_y	0.483***	0.631***	0.061	-0.221**
After X POG_Goat_y	0.307**	0.401***	0.074	-0.187*
After X POG_Draft_y	0.342	0.222	0.126*	0.008
After X POG_Dairy_n	0.143	0.011	0.187***	-0.063
After X POG_Goat_n	0.104	0.131	0.034	-0.078
After X POG_Draft_n	0.062	0.025	0.078	-0.035
After X Independent	0.013	0.07	0.002	-0.063
G* After x_Dairy	0.562	0.134	0.12	0.343
G* After x_Goat	0.326	-0.215	0.291**	0.232
G* After x_Draft	0.535	-0.175	0.148	0.557
G* After x POG_Dairy_y	-0.032	0.29	0.003	-0.231
G* After x POG_Goat_y	-0.622	-0.547*	-0.296**	0.297
G* After x POG_Draft_y	-0.924	0.469	-0.224	-1.203*
G* After x POG_Dairy_n	0.111	-0.555	0.141	0.628
G* After x POG_Goat_n	-0.336	-0.557	-0.092	0.395
G* After x POG_Draft_n	-0.903	-0.226	0.107	-0.828*
G* After x Independent	-0.024	0.236	-0.174	0.029
W* After x_Dairy	-0.64*	-0.778***	0.066	0.045
W* After x_Goat	-0.617***	-0.473***	-0.073	-0.08
W* After x_Draft	-0.959**	0.045	-0.206	-0.789***
W* After x POG_Dairy_y	0.031	0.05	-0.128	0.109
W* After x POG_Goat_y	0.378	0.293	-0.067	0.102
W* After x POG_Draft_y	0.595	-1.075*	0.196	1.408***
W* After x POG_Dairy_n	-0.046	0.492*	-0.169	-0.38
W* After x POG_Goat_n	-0.285	-0.093	0.38	-0.374
W* After x POG_Draft_n	1.527**	-0.211	0.488**	1.212**
W* After x Independent	1.014	0.786	0.17	0.196
ρ	0.283***	0.037	0.36***	0.004
Observations	2056	2056	2056	2056

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome variables are log weekly per capita consumption value, adjusted to 2012 ZMK values

Suppressed household, village, and time FE, clustered SE, and positive/negative HH shocks

Table 5: Spillover Effect Estimation: Meat Consumption Value

	(1) Total Expenditure	(2) Production	(3) Gifts	(4) Purchases
After x Dairy	0.637***	0.320**	-0.076	0.408**
After x Goat	0.819***	0.433***	0.100	0.335*
After x Draft	0.528**	0.263*	-0.200*	0.521**
After x POG_Dairy_y	0.488**	0.300**	-0.065	0.246
After x POG_Goat_y	0.855***	0.397***	0.094	0.392**
After x POG_Draft_y	0.709**	0.224	-0.046	0.578**
After x POG_Dairy_n	0.589***	0.286**	-0.107	0.443**
After x POG_Goat_n	0.895***	0.408***	0.226**	0.303
After x POG_Draft_n	0.319	0.293*	-0.090	0.187
After x Independent	0.450**	0.312**	-0.080	0.257
G * After x Dairy	0.444	0.025	-0.218	0.602
G * After x Goat	0.112	-0.212	0.210	0.012
G * After x Draft	1.658	-0.499	-0.444	2.593**
G * After x POG_Dairy_y	0.809	-0.009	0.421	0.597
G * After x POG_Goat_y	0.289	-0.903**	-0.204	1.428***
G * After x POG_Draft_y	0.814	-0.476	0.952	0.326
G * After x POG_Dairy_n	-2.025**	0.099	-0.523	-1.505*
G * After x POG_Goat_n	-1.592	-0.593	-0.775*	-0.211
G * After x POG_Draft_n	-1.321	-0.036	0.019	-1.429*
G * After x Independent	-1.009	-0.372	-0.159	-0.435
W * After x Dairy	0.317	-0.354	0.004	0.599
W * After x Goat	-0.578**	-0.429**	-0.174	-0.021
W * After x Draft	-1.147**	-0.294	-0.067	-0.881*
W * After x POG_Dairy_y	-0.535	0.139	0.125	-0.812**
W * After x POG_Goat_y	-0.072	0.006	0.363	-0.553
W * After x POG_Draft_y	0.205	0.225	0.205	-0.171
W * After x POG_Dairy_n	-0.302	0.117	0.296	-0.708*
W * After x POG_Goat_n	-0.223	1.593*	-0.796	-0.532
W * After x POG_Draft_n	1.081	0.483	0.408	0.240
W * After x Independent	1.120	-0.472	0.585	1.125
ρ	0.433***	-0.070	0.148	0.207*
Observations	2056	2056	2056	2056

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome variables are log weekly per capita consumption value, adjusted to 2012 ZMK values

Suppressed household, village, and time FE, clustered SE, and positive/negative HH shocks

Appendix

A Description of Variables

Adjustment to monetary variables:

On January 1st, 2013, the Zambian kwacha was redenominated to address persistent inflation. The old currency unit was divided by 1000 to yield the new unit of kwacha (ZMK). During Rounds 1-4, the survey reported values in the old currency system and thus these values were adjusted to the new system by dividing by 1000 in order to compare to Rounds 5-8. Round 3-8 were deflated using inflation rates provided by the World Bank to represent 2012 values (Round 1 and 2). USD dollar equivalents are provided using purchasing power parity (PPP) conversions provided by the World Bank.

FAO recommends the use of a Household Dietary Diversity Score (HHDDS) which is generated by surveying households on which food groups they consume over a given period and counting the number of food groups which are met. It is recommended to use 24 hour recall and surveying the household over multiple seasons. (Carletto et al., 2017; FAO, 2010; Engle-Stone et al., 2017) Another possibility is a Food Consumption Score (FCS) which is a mean of food items consumed, but does not have contextualized cutoff points or use food groups.(FAO, 2010) Hoddinot and Yohannes (1999) showed that a 1 percent increase in dietary diversity is associated with a 1 percent increase in per capita consumption and 0.7 percent increase in total per capital calorie availability Ruel (2003) added that dietary diversity is not a measure of dietary quality, but is correlated with food security. In this paper, I use a household dietary diversity measure that follows the FAO recommendation, but combines certain items to yield 13 groups instead of 16 groups. The 13 food groups are vegetables, beverages/sweets, cereals, white tuber, yellow/orange tuber, orange/red flesh fruits, other fruits, meat/chicken, eggs, fish legumes/nuts/seeds, milk and milk products, and oils. Consumption frequency is measured as the number of days the household reports consuming specific items from these food groups over a seven day period.

Household expenditures are typically used to capture household wealth and poverty status. The CRLESP project measured total household expenditure, as well as aggregates of expenditures on food and non-food items, and expenditures on specific categories of food groups. The food expenditure aggregate includes food that the household purchases, produces at home, or is gifted by another household.

Expenditure variables:

$foodexp$ is the weekly amount in kwacha the household spent in the prior week on 13 food group items, which are then aggregated to form total weekly food expenditure by the household. $foodexp_{wkpc}$ is the total weekly food expenditures divided by household size.

$nonfoodexp$ is the Kwacha value of household spending on an aggregate of all purchased non-food items. $nonfoodexp_{wkpc}$ is the total weekly nonfood expenditures divided by the household size. The survey asks about purchases during the past 3 months, which is then divided by 12 to determine the weekly non food expenditure for the household. Categories include clothing, kitchen equipment, bedding, furniture, electrical, building, transportation, ceremonial, church offerings,taxes, medicine, school fees and materials, alcohol, tobacco, and other consumable goods.

$totexp$ is is the weekly amount spent by the household on both food and nonfood items, calculated as the aggregate of weekly $foodexp$ and weekly $nonfoodexp$. $totexp_{wkpc}$ is the total expenditure, divided by household size.

All expenditure variables are adjusted to 2012 values and are winsorized at the 99% level to eliminate outliers. Missing nonfood expenditures were imputed using household characteristics and expenditure levels in the prior round.

$Foodshare$ is weekly household food expenditures divided by weekly household total expenditures. $ASFshare$ is weekly household meat and milk expenditures divided by weekly household total expenditures.

Value of Consumption variables:

The value of consumption of each category within milk, meat, oil, sweets/beverages, rice, and maize, is constructed as the aggregate of the total amount reported purchased, gifted, or consumed from home production by the household on a weekly basis. The value of the home produced and gifted amounts is calculated using 2012 ZMK values for comparative purposes. The value of purchased amounts is reported by the households, and then deflated to 2012 ZMK values. The consumption values are then divided by household size to yield weekly consumption per capita values.

There are two survey-based quirks related to consumption variables. The first round of survey collection aggregated meat, chicken, fish, and dried fish into a single category. This was disaggregated in subsequent rounds. Thus any estimates using meat consumption value as a dependent variable should be conservative estimates, as the baseline consumption value is inflated. The survey instrument in the first four rounds asks: total consumption quantity, the distinct percentages from production/gifts/purchases, and the cost of purchases. However, enumerators turned the percentage question into a binary yes/no, and thus it is not possible to separate the consumption quantity into the three categories. Therefore in all rounds, the coding has been to count purchases only if production or gift is not selected. There is an obvious bias here that cannot be remediated.

Livestock variables:

herdsize is the total number of livestock owned by the household converted into tropical livestock units (TLU), a standardization determined by FAO based on livestock size. Number of cattle and goats are reported by the household.

livstksales is the total value of livestock sold during the prior three months by the household *livstkprodsales* is the total value of livestock products (meat, milk, eggs, manure, or draft labor) sold during the prior three months by the household. *livstkrev* is the aggregate of the two type of livestock sales, which is then divided by *householdsize* to yield $livstkrev_{wkpc}$, which is per capita weekly livestock revenue. All variables are adjusted to 2012 values. $livstkrev_{w}kpc$ is winsorized at the 99 % level.

Household Characteristics:

Total land is the total area in hectares that the household planted during the prior three months as the aggregate of the land cultivated by crop

HH Durable assets are an aggregate of all permanent assets owned by the household. This is winsorized at the 99 % level. *TV* and *bicycle* ownership are binary variables equal to 1 if the household reports ownership, and 0 otherwise.

Education level of the household head is a step scale from 0 for no education, to 6 for Tertiary University ($>$ 3 years)

Gender and *Marital Status* are also identified for the head of the household, and are binary variables.

Dependency ratio is the ratio of number of children under 16 to the total *householdsize*.

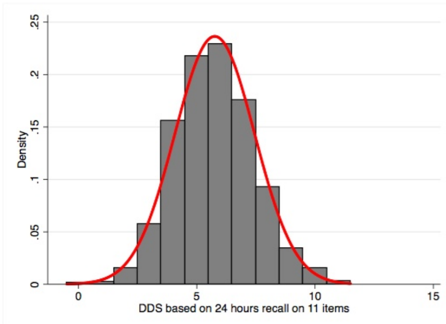
Food Security and Consumption Variables:

foodsecure is a dummy representing 0 if the household reports feeling more insecure than 6 months ago and 1 if the household reports feeling less secure than 6 months ago

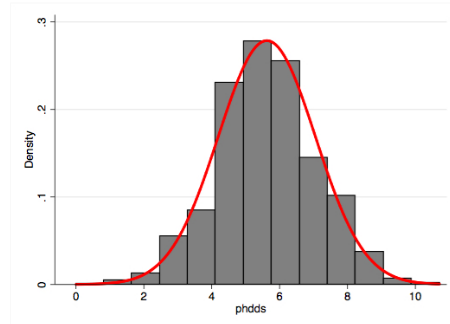
FeelingPoor is a dummy representing 0 if the household reports feeling worse off than 6 months ago and 1 if the household reports the same or better off than 6 months ago.

hdds is a household dietary diversity measure using 24-hour recall respectively. The survey instrument asked households whether they had consumed items within 13 categories during the previous 24 hours, consistent with FAO methodology: Cereals, White tubers and roots, Yellow tubers and roots, Vegetables, Fruits orange or red flesh, Fruit other, Meats, Eggs, Fish and other seafood, Milk and milk products, Legumes nuts seeds, Oils and Fats, and Sweets spices condiments and beverages. There were no households in the sample who answered “No” to all food groups in the 24-hour recall. Because a household may consumer a category weekly but not daily, a probability based dietary recall (HHDDSprob) was developed to address these patterns using data from a seven day recall. The probability was calculated as: $\sum_{i=1}^{13} \frac{n_i}{7}$ where n is the number of times per week food category i was consumed.

As household dietary diversity is technically a count variable, other functional forms might be required. However, the distributions of both the HHDDS and HHDDSprob variables were normal.



(a) HH dietary diversity



(b) Probability weighted HDDS

Figure A.1: Distribution of count variables

The frequency of consumption is reported as the number of days within the past week the household reported serving each of the following categories: $milk, meat, cereals, sweets/beverages, and oil$.

Table A.1: Replication Outcome Variables at Baseline by Treatment Type

	Original	POG	Independent	Prospective	Orig v. Pros	POG v. Pros	Indp v. Pros
Weekly expenditure per cap 2012 ZMK	31.17	33.90	28.39	45.04	13.87**	11.14*	16.65***
	(19.10)	(28.16)	(18.35)	(30.89)			
Weekly expenditure per cap 2012 USD	12.47	13.56	11.36	18.02	5.551**	4.458*	6.663***
	(7.641)	(11.27)	(7.342)	(12.36)			
Food share as % of expenditure	0.546	0.560	0.619	0.543	-0.003	-0.018	-0.076*
	(0.167)	(0.188)	(0.178)	(0.169)			
ASF share as % of expenditure	0.139	0.142	0.177	0.157	0.018	0.0153	-0.020
	(0.121)	(0.118)	(0.157)	(0.119)			
Weekly Livestock revenue per cap 2012 ZMK	2.809	3.932	1.126	8.378	5.569	4.446	7.252*
	(8.365)	(10.86)	(2.530)	(26.49)			
DDS based on 24hr recall on 13 items	5.783	5.685	5.625	5.627	-0.156	-0.058	0.002
	(1.937)	(1.612)	(1.409)	(1.921)			
Days milk served/week	1.283	1.126	0.725	1.716	0.433	0.590	0.991*
	(2.097)	(2.068)	(1.536)	(2.707)			
Days meat served/week	1.009	1.216	0.775	1.209	0.200	-0.007	0.434*
	(0.941)	(1.404)	(0.832)	(1.274)			
Feeling poor (1=Yes,0=No)	0.632	0.730	0.850	0.866	0.234***	0.136*	0.016
	(0.485)	(0.446)	(0.362)	(0.344)			
Food Secure (1=Yes,0=No)	0.368	0.378	0.325	0.373	0.005	-0.005	0.048
	(0.485)	(0.487)	(0.474)	(0.487)			
Observations	106	111	40	67			

Point estimates are mean; Standard deviations are in parentheses; the last three columns contain the difference between group means and their significance

2012 USD PPP values are using World Bank conversion factor

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Replication of Prior Results

Two prior papers have identified causal results from the first four rounds of this data set: Jodlowski used a difference-in-difference (DiD) model and found increases in expenditure per capita for all treatment households, increases in probability weighted household dietary diversity for goat and dairy cow households, and increases in the value of milk consumption for POG households in dairy cow and draft cow villages. Kafle also used a DiD model and quasi maximum likelihood (MLE) to find similar increases in food and nonfood expenditures and livestock revenues, increases in the consumption of milk, and decreases in the subjective measures of poverty by all treatment households. Kafle also found significant increases in the value and frequency of milk consumption by POG households. Kafle included the independent households in his analysis, whereas Jodlowski did not, although they are not intended to be a control or treatment group.

Extension of the methodology used by Jodlowski and Kafle to all eight rounds is instructive because the first four rounds occurred during the initial 18 months of the program, while the final round (Round 8) occurred a full 5.5 years after the initial distribution of animals to Original households. The persistence or decline of treatment effects over time can yield a better estimate of the medium-term impact of livestock donation on rural households. Tables A.2 and A.3 present the results of the replication and extension exercise. The dark grey rows are results from the original estimation by Jodlowski/Kafle for Rounds 1-4, the light grey rows are results from my replication of those models for Rounds 1-4, and the white row are results from my replication of those models for Rounds 1-8.

The results of the extension to Rounds 1-8 for expenditure and revenue outcomes are presented in Table A.2 . All outcome variables are log-transformed to yield a smoother distribution and the models are noted in the footnotes. When POG households are separated from prospective households (K1), total weekly expenditures per capita increased by about 30% for dairy cow recipients, 33% for draft cattle recipients and 36% for meat goat recipients, and 17% for POG households that received livestock. These effects were driven by increases in both food and non-food expenditures for all recipients. For draft households, the increase in nonfood expenditure is more than three times that of food expenditure, supporting the hypothesis that those households are not shifting wealth increases into consumption. The results are slightly larger after 5.5 years (Rounds 1-8) than after 18 months of the program (Rounds 1-4), indicating that the program had a significant and persistent impact on total weekly household expenditure per capita.

After eight rounds, the value of milk consumption per capita increased by about 80% for dairy cow households and 40% for POG recipient households. This effect is smaller than the effects seen after Round 4 for treatment households, which may be due to aging of animals. Meat consumption per capita increased by 50% for dairy cow households, 100% by meat goat households, and about 60% for POG recipient and non-recipient households. This effect was similar to the effect seen after Round 4. Consumption of oil and sweets increased for both dairy cow and meat goat households, while only draft cattle and meat goat households saw increases in rice consumption. These effects were consistent and persistent from 18 months to 5.5 years. Livestock revenue increased by over 400% for dairy cow households and 95% by draft cattle households, but there were no significant increases for meat goat households. These effects were consistent and persistent from Round 4 to Round 8. Based on the increase in meat consumption by meat goat households, it seems likely that those households chose to consume rather than sell their goats, while the dairy cow households were able to increase both consumption of milk and livestock revenue simultaneously.

One way to measure spillover effects is through the effects on POG households. As these household live in recipient villages, and eventually are intended to receive animals, spillovers might occur indirectly through increased availability of milk and meat in villages, or directly through livestock ownership. The significance of increases in food expenditures, and milk consumption for POG_y households relative to POG_n households supports the hypothesis that it is the direct effect of livestock ownership that yields benefits. However the increase in the value of meat consumption is almost equivalent for POG_y and POG_n households, which may mean that more meat is now availably in the villages. Delineating this effect by village (dairy v. draft v. goat) would help disentangle this effect.

The results of the extension to Rounds 1-8 for frequency and binary outcomes are presented in Table A.3, with the specific models noted in the footnotes. Household dietary diversity is measured in the number of food groups out of 13 consumed by the household in the prior 24 hours. Consumption frequency is number of days per week the food group was consumed by the household. When POG households are separated from prospective households (K2), household dietary diversity increased by a little over one food group per day for dairy cow and draft cattle recipients, ($e^{0.18} = 1.2$ and $e^{0.12} = 1.1$ respectively), representing about a 20% increase from the mean dietary diversity of 5.78 food groups per day for both types of households. These effects are consistent and persistent from 18 months to 5.5 years, suggesting that meat goat recipients are least likely to diversify their diet due to the program. After 5.5 years, milk consumption increased more than four days per week for dairy cow households, 1.6 days per week for draft cattle households, 1.4 days per week for meat goat households, and 2.2 days per week for POG households. The effects for dairy, draft, and goat households reduced over time, while the effect for POG_y households persisted, supporting the hypothesis that animals are aging. Meat consumption increased by 1.4 days per week for meat goat households and was persistent from Rounds 1-4 to Rounds 1-8. No significant effects were seen for cereal, oil, or sweets/beverage consumption categories, which is not necessarily consistent with the consumption changes for meat goat households. This may be due to relative price increases for those categories compared to meat and milk products.

For the subjective poverty measures, the probability of feeling poor after 5.5 years decreased among dairy and draft household, but not meat goat households. These results were stronger through Round 4, but still significant through Round 8. The probability of feeling poor increased among POG households through Round 4, likely attributable to the increase for POG_n households identified through Round 8. Through Round 4, dairy households reported feeling more food secure, however through Round 8, there were no significant changes for any treatment households. Both types of POG households reported feeling less food secure through Round 8, with the largest change for POG_n, possibly because they consider themselves relatively poor by the end of the program, having still not received any animals.

Table B.1: Summary of Replication and Extension of Expenditure and Revenue Outcome Variables

Model	Outcome Variable	Round	After x Dairy	After x Draft	After x Goat	After x Pog	After x Pog_y	After x Pog_n
J1	Total Expenditure per capita (Log, ZMK/week)	1-4	0.229**	0.262**	0.215**			
		1-4	0.185	0.224*	0.212**			
		1-8	0.223*	0.250**	0.273***			
J2		1-4	0.271**	0.303**	0.256**	0.068		
		1-4	0.119	0.184	0.164*	0.019		
		1-8	0.315**	0.341***	0.365***		0.175*	0.130
K1	Total Expenditure per capita (Log, ZMK/week)	1-4	0.241**	0.277**	0.202*	0.080		
		1-4	0.226*	0.260**	0.252***	0.065		
		1-8	0.308**	0.329***	0.360***		0.173*	0.117
K1	Food Expenditure per capita (Log, ZMK/week)	1-4	0.363***	0.208	0.220*	0.152		
		1-4	0.337***	0.180	0.257**	0.122		
		1-8	0.256*	0.155*	0.327***		0.186*	0.115
K1	Non-food Expenditure per capita (Log, ZMK/week)	1-4	-0.078	0.413**	0.203	0.010		
		1-4	0.008	0.331*	0.218*	0.013		
		1-8	0.322**	0.552***	0.382***		0.176	0.151
J1*	Milk Consumption Value by Household (ZMK/week)	1-4	20.310***	16.175**	2.618			
		1-4	11.273***	6.046	1.438			
		1-8	6.076***	0.907	-1.415			
K1	Milk Consumption per capita (Log, ZMK/week)	1-4	4.210***	0.836	1.070	1.152**		
		1-4	0.817***	0.291*	0.244**	0.215***		
		1-8	0.592***	0.159	0.137		0.322***	0.030
K1	Meat Consumption per capita (Log, ZMK/week)	1-4	0.478	0.716	0.805	0.878*		
		1-4	0.290	0.528	0.577***	0.356**		
		1-8	0.404*	0.384	0.745***		0.466***	0.476***
K1	Oil Consumption per capita (Log, ZMK/week)	1-4	0.456	0.242	0.307	0.286		
		1-4	0.237**	0.148*	0.153**	0.128**		
		1-8	0.269***	0.111	0.190**		0.056	0.132*
K1	Sweets/Beverages Consumption per capita (Log, ZMK/week)	1-4	0.911**	-0.119	0.278	-0.033		
		1-4	0.466***	-0.081	0.284**	0.047		
		1-8	0.480***	0.091	0.359***		0.113	-0.014
K1	Rice Consumption per capita (Log, ZMK/week)	1-4	0.433	2.298***	1.253*	0.528		
		1-4	0.030	0.435***	0.269**	0.053		
		1-8	-0.025	0.322***	0.274***		0.025	-0.049
K1	Maize Consumption per capita (Log, ZMK/week)	1-4	1.119**	0.187	0.044	0.650***		
		1-4	0.137	0.051	0.039	0.151*		
		1-8	0.007	-0.027	-0.018		0.058	0.094
K1	Livestock Revenue per capita (Log, ZMK/week)	1-4	7.009***	1.667**	-0.437	-0.478		
		1-4	1.777***	0.731***	-0.020	-0.174		
		1-8	1.641***	0.666***	0.281		0.200	-0.140

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model J1: $y_{ilt} = \alpha_0 + \sum_l \beta_l A_t T_{il} + \sum_t \gamma_t A_t + \sum_l \delta_l T_{il} + \mu X_{ilt} + FE_i + \varepsilon_{ilt}$

where $A_t T_{il}$ is an interaction between A_t an indicator for after treatment (0 if $t = 1$, 1 otherwise) and T_{il}, an indicator equal to 1 if household$i$ received species l and 0 if prospective

X_{ilt} are covariates: household size, dependency ratio, and positive and negative household shocks.

For J1*, X_{ilt} also includes log weekly total household expenditure per capita

Model J2: Model J1 where Treatment now includes livestock-specific treatment and POG households

Model K1: Model J2 where X_{ilt} is a covariate vector: gender and marital status of household head, and positive and negative shocks

Table B.2: Summary of Replication and Extension of Frequency Variables

Model	Outcome Variable	Round	After x Dairy	After x Draft	After x Goat	After x Pog	After x Pog_y	After x Pog_n
J1	Probability-Weighted Household Dietary Diversity	1-4	0.633***	-0.130	0.404**			
		1-4	0.633***	-0.130	0.404**			
		1-8	0.212	-0.398*	0.449**			
J2		1-4	0.575**	-0.282	0.356	-0.117		
		1-4	0.575***	-0.187	0.346*	-0.094		
		1-8	0.137	-0.473*	0.374*		0.002	-0.282
J1	Household Dietary Diversity	1-4	0.248	-0.564*	0.303			
		1-4	0.301	-0.426	0.309			
		1-8	0.322	-0.894**	0.547**			
K2	Household Dietary Diversity	1-4	0.200***	0.207***	0.008	0.057		
		1-4	0.179***	0.161***	-0.054	0.008		
		1-8	0.182***	0.121***	-0.017		0.034	0.015
K2	Milk consumption (number of days/week)	1-4	1.570***	0.765***	0.685***	0.478***		
		1-4	1.785***	0.620**	0.711***	0.653***		
		1-8	1.421***	0.477*	0.366*		0.770***	0.032
K2	Meat consumption (number of days/week)	1-4	0.036	-0.026	0.339***	0.019		
		1-4	0.031	-0.002	0.287**	-0.110		
		1-8	0.035	0.010	0.321***		0.131	0.018
K2	Cereal consumption (number of days/week)	1-4	-0.003	0.020	-0.002	-0.000		
		1-4	0.001	0.010	-0.008	-0.003		
		1-8	-0.001	-0.008	-0.010		-0.010*	-0.007
K2	Oil consumption (number of days/week)	1-4	0.034	0.024	-0.030	-0.014		
		1-4	0.048**	0.009	-0.046	-0.028		
		1-8	0.030	0.026	-0.006		0.012	-0.014
K2	Sweets/beverages consumption (number of days/week)	1-4	0.189***	0.150**	0.066	0.031		
		1-4	0.158**	0.096	0.043	-0.046		
		1-8	0.125*	0.134	0.093		0.089	-0.006
K3	Feeling poor (=1 if feel relatively worse and =0 if same or better	1-4	-1.360***	-0.694***	-0.339**	0.153		
		1-4	-0.836***	-0.598***	0.053	0.313**		
		1-8	-0.743***	-0.421**	0.051		0.021	0.414***
K3	Food Secure (=1 if feel secure and =0 if feel otherwise)	1-4	0.594***	0.181	0.068	-0.09		
		1-4	0.612***	0.150	-0.043	-0.190		
		1-8	0.193	0.107	-0.124		-0.217*	-0.528***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dark Grey row values are original estimates from Jodlowski/Kafle using rounds 1-4.

Light grey values are Cardell replication using round 1-4 data, and white row values are using round 1-8 data

Model J1: $y_{ilt} = \alpha_0 + \sum_l \beta_l A_t T_{il} + \sum_t \gamma_t A_t + \sum_l \delta_l T_{il} + \mu X_{ilt} + FE_i + \varepsilon_{ilt}$

where $A_t T_{il}$ is an interaction between A_t an indicator for after treatment (0 if $t = 1$, 1 otherwise) and T_{il}, an indicator equal to 1 if household$i$ received species l and 0 if prospective

X_{ilt} are covariates: log weekly total expenditure per capita, household size, dependency ratio, and positive and negative household shocks.

Model J2: Model J1 where Treatment now includes POG households

Model K2: $E(y_{ilt} \mid x_{ilt}, \bar{x_{il}}) = exp(\sum_l \beta_l A_t T_{il} + \sum_t \gamma_t A_t + \sum_l \delta_l T_{il} + \gamma POG_{it} + \lambda Indp_{it} + \pi X + \theta \bar{X})$

X is a covariate vector: household size, number of children 5 or under, age, hh head gender, marital status, number of sheep, number of pigs, and positive and negative shocks

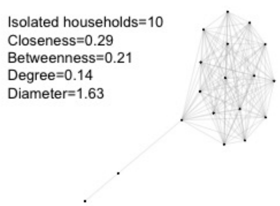
Model K3: $P(y_{ilt} \mid x_{ilt}, \bar{x_{il}}) = \Phi(\sum_{l=1}^{3} \beta_l A_t T_{il} + \sum_{t=2}^{4} \gamma_t A_t + \sum_{l=1}^{3} \delta_l T_{il} + \gamma POG_{it} + \lambda Indp_{it} + \pi X + \theta \bar{X})$

X is a covariate vector: household size, number of children 5 or under, age, hh head gender, marital status, number of sheep, number of pigs, and positive and negative shocks

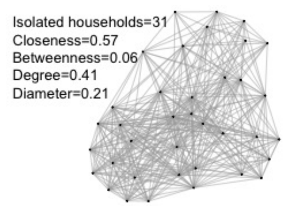
C Social Network Graphs

Table C.1: Participation in Social Groups by Village

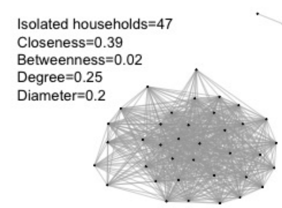
community	N	livestock	crop	fishing	forest	water	insurance	trade	govt	civic	microfinance	religious	mens	womens
Chembe	29	0.28	0.31	0.03	0.07	0.03	0.00	0.03	0.55	0.55	0.24	0.24	0.14	0.34
Kamisenga	79	0.44	0.22	0.08	0.16	0.09	0.06	0.04	0.24	0.34	0.10	0.38	0.03	0.13
Kanyenda	101	0.49	0.40	0.02	0.15	0.02	0.03	0.04	0.21	0.32	0.11	0.42	0.05	0.29
Kaunga	52	0.33	0.15	0.02	0.21	0.10	0.06	0.10	0.40	0.44	0.19	0.40	0.12	0.31
Mwanaombe	30	0.20	0.57	0.03	0.07	0.00	0.00	0.03	0.03	0.37	0.17	0.40	0.07	0.30
Total	291	0.40	0.31	0.04	0.15	0.05	0.04	0.05	0.27	0.37	0.14	0.38	0.07	0.25



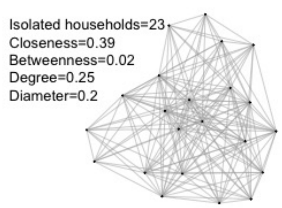
(a) Chembe



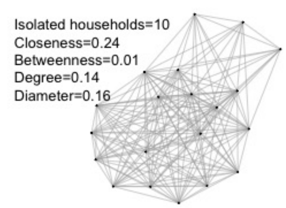
(b) Kamisenga



(c) Kanyenda



(d) Kaunga



(e) Mwanaombe

Figure C.1: Social Connections by Village

D Market Price Analysis

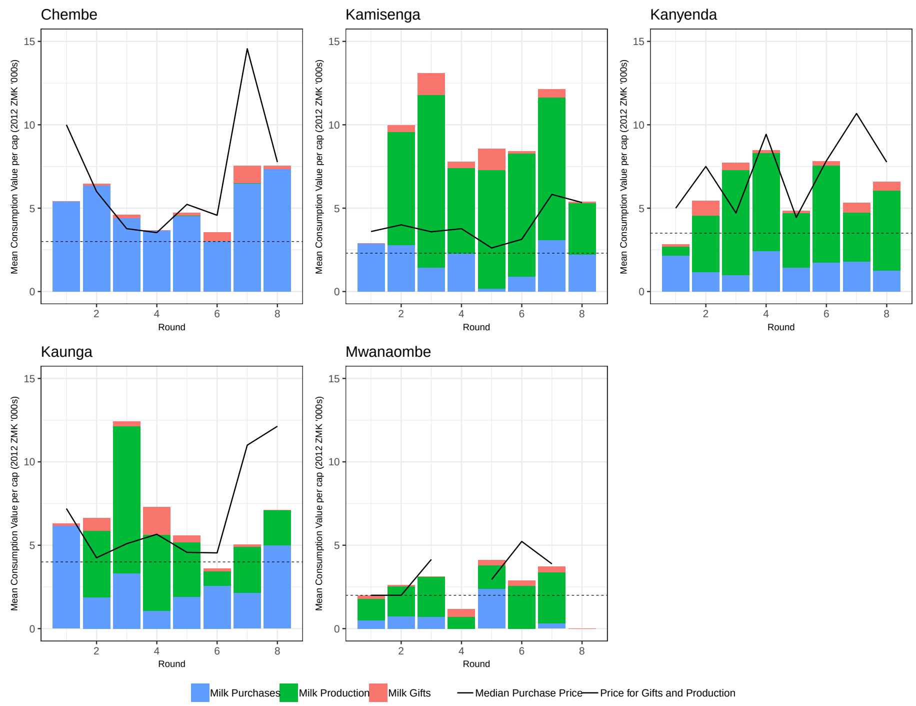


Figure D.1: Milk Consumption Value by Village and Round

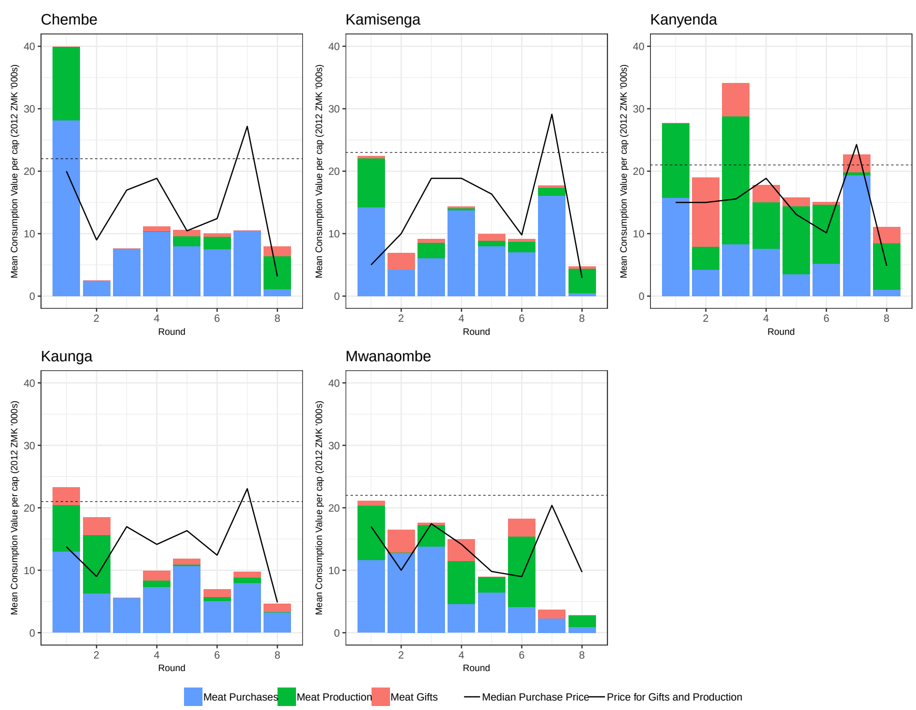


Figure D.2: Meat Consumption Value by Village and Round

Table D.1: Inflation by Round and Community and Treatment

	Dependent variable:			
	Milk Price		Meat Price	
	(1)	(2)	(3)	(4)
Chembe	17.488***	17.488***	18.994***	18.994***
Kamisenga	5.569**	5.569**	8.152***	8.152***
Kanyenda	9.019***	9.019***	13.635***	13.635***
Kaunga	13.882***	13.882***	17.559***	17.559***
Mwanaombe	2.000	2.000	17.604***	17.604***
treatall*Chembe				
treatall*Kamisenga		0.021		5.998***
treatall*Kanyenda		−0.964		−1.828
treatall*Kaunga		2.581		3.594*
treatall*Mwanaombe				
Round 2	−8.306*	−8.306*	−8.669*	−8.669*
Round 3	−7.621*	−7.621*	−3.394	−3.394
Round 4	−11.301***	−11.301***	2.106	2.106
Round 5	−9.573**	−9.573**	−4.131	−4.131
Round 6	−10.152**	−10.152**	−1.298	−1.298
Round 7	7.057	7.057	5.434	5.434
Round 8	−8.758**	−8.758**	−14.244***	−14.244***
Round 2*Kamisenga	8.469	8.468	10.981**	7.805
Round 2*Kanyenda	8.454	8.776	8.201	9.318*
Round 2*Kaunga	2.108	1.678	4.137	2.503
Round 2*Mwanaombe	9.706	9.706	0.440	0.440
Round 3*Kamisenga	6.691	6.686	15.045***	11.671***
Round 3*Kanyenda	11.403	12.174	6.430	8.038*
Round 3*Kaunga	3.534	2.243	3.078	1.444
Round 3*Mwanaombe	10.021	10.021	3.442	3.442
Round 4*Kamisenga:	9.777*	9.768	11.500***	7.138*
Round 4*Kanyenda	14.827***	15.534**	2.292	3.643
Round 4*Kaunga	13.453**	11.905*	−3.408	−5.804
Round 4*Mwanaombe			−4.877	−4.877
Round 5*Kamisenga	8.003	8.003	18.155***	14.156***
Round 5* Kanyenda	13.281**	14.019**	6.996*	8.693*
Round 5*Kaunga	10.829*	9.109	11.750***	9.183**
Round 5*Mwanaombe	12.573	12.573	−0.074	−0.074
Round 6*Kamisenga	9.771	9.764	9.396**	5.034
Round 6*Kanyenda	15.335***	16.230**	5.063	6.891
Round 6*Kaunga	7.061	5.184	3.281	0.585
Round 6*Mwanaombe			−5.794	−5.794
Round 7*Kamisenga	−7.254	−7.264	16.293***	11.930***
Round 7*Kanyenda	−5.002	−4.252	4.312	5.980
Round 7*Kaunga	0.228	−2.353	1.507	−0.740
Round 7*Mwanaombe	−5.057	−5.057	1.962	1.962
Round 8*Kamisenga	10.096*	10.083	12.493**	7.694
Round 8*Kanyenda	8.168	8.994	7.235	9.062
Round 8*Kaunga	8.967	7.091	3.857	1.803
Round 8*Mwanaombe			6.640	6.640
Observations	355	355	576	576
Note:	*p<0.1; **p<0.05; ***p<0.01 treatall = 1 if HH received an animal			

Bibliography

Alkire, S., Meinzen-Dick, R., Peterman, A., Quisumbing, A., Seymour, G. and Vaz, A. (2013), 'The Women's Empowerment in Agriculture Index', *World Development* **52**, 71–91.

Angrist, J. D. (2014), 'The perils of peer effects', *Labour Economics* **30**, 98–108.

Anselin, L. (2001), 'Spatial econometrics', *A companion to theoretical econometrics* pp. 310–330.

Baird, S., Hicks, J. H., Kremer, M. and Miguel, E. (2016), 'Worms at work: Long-run impacts of a child health investment', *Quarterly Journal of Economics* **131**(4), 1637–1680.

Baltagi, B. H., Song, S. H. and Koh, W. (2003), 'Testing panel data regression models with spatial error correlation', *Journal of Econometrics* **117**(1), 123–150.

Baylis, K. R., Paulson, N. D. and Piras, G. (2011), 'Spatial Approaches to Panel Data in Agricultural Economics: A Climate Change Application', *Journal of Agricultural and Applied Economics* **43**(03), 325–338.

Beaman, L., Benyishay, A., Magruder, J., Mobarak, A. M., Coen, T., Kelleher, N., Jones, M., Cohen, O. and Baumgardner-Zuzik, A. (2018), Can Network Theory-based Targeting Increase Technology Adoption?

Bramoullé, Y., Djebbari, H. and Fortin, B. (2009), 'Identification of peer effects through social networks', *Journal of Econometrics* **150**(1), 41–55.

Carletto, C., Corral, P. and Guelfi, A. (2017), 'Agricultural commercialization and nutrition revisited: Empirical evidence from three African countries', *Food Policy* **67**, 106–118.

Chandrasekhar, A. G., Larreguy, H. and Xandri, J. P. (2016), 'Testing Models of Social Learning on Networks', *National Bureau of Economic Research* pp. 1–54.

Chuang, Y. and Schechter, L. (2015), Social Networks in Developing Countries.

Conley, T. G. and Udry, C. R. (2010), 'American Economic Association Learning about a New Technology: Pineapple in Ghana Learning about a New Technology: Pineapple in Ghana', *American Economic Review* **100**(1001), 35–69.

De Giorgi, G., Pellizzari, M. and Redaelli, S. (2010), 'Identification of Social Interactions through Partially Overlapping Peer Groups', *American Economic Journal: Applied Economics* **2**(2), 241–275.

de Janvry, A., Dustan, A., Sadoulet, E., Janvry, a. D., Dustan, A. and Sadoulet, E. (2010), Recent advances in impact analysis methods for ex-post impact assessments of agricultural technology: Options for the CGIAR, Technical Report April.

de Janvry, A., Fafchamps, M. and Sadoulet, E. (1991), 'Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained', *The Economic Journal* **101**(409), 1400.

Doss, C. R. and Mcpeak, J. G. (2005), 'Are Household Production Decisions Cooperative? Evidence on Pastoral Migration and Milk Sales from Northern Kenya'.

Engle-Stone, R., Sununtnasuk, C. and Fiedler, J. L. (2017), 'Investigating the significance of the data collection period of household consumption and expenditures surveys for food and nutrition policymaking: Analysis of the 2010 Bangladesh household income and expenditure survey', *Food Policy* **72**(September), 72–80.

FAO (2010), *Guidelines for measuring household and individual dietary diversity*.

FAO, IFAD, WFP and WHO (2017), 2017 BUILDING RESILIENCE FOR PEACE AND FOOD SECURITY THE STATE OF FOOD SECURITY AND NUTRITION IN THE WORLD, Technical report.

fei Lee, L. and Yu, J. (2010), 'Estimation of spatial autoregressive panel data models with fixed effects', *Journal of Econometrics* **154**(2), 165–185.

Guryan, J., Kroft, K. and Notowidigdo, M. J. (2009), 'Peer effects in the workplace: Evidence from random groupings in professional golf tournaments', *American Economic Journal: Applied Economics* **1**(4), 34–68.

Headey, D., Hirvonen, K. and Hoddinott, J. (2018), 'Animal Sourced Foods and Child Stunting', *American Journal of Agricultural Economics* **100**(5), 1302–1319.

Hoddinott, J., Headey, D. and Dereje, M. (2015), 'Cows, Missing Milk Markets, and Nutrition in Rural Ethiopia', *Journal of Development Studies* **51**(8), 958–975.

Hoddinott, J. and Yohannes, Y. (1999), Dietary Diveristy as a Food Security Indicator.

James Heckman, U. J., Lochner, L., Taber, C., Becker, G., Hansen, L., Katz, L., Klenow, P., Levitt, S., Mulligan, C., Neal, D., Rosen, S., Trefler, D., Siow, A. and Yorukoglu, M. (1998), 'Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents Young for their helpful comments. We thank Eric Engen and Peter Klenow for giving us data on capital, capital shares, and', *Review of Economic Dynamics* **1**.

Jodlowski, M., Winter-Nelson, A., Baylis, K. and Goldsmith, P. D. (2016), 'Milk in the Data: Food Security Impacts from a Livestock Field Experiment in Zambia', *World Development* **77**, 99–114.

Kafle, K., Michelson, H. and Winter-Nelson, A. (2018), 'His, Hers, or Ours: Impacts of a Training and Asset Transfer Program on Intra-household Decision-making in Zambia 1 Kashi Kafle', *The Journal of Development Studies* pp. 1–39.

Kafle, K., Winter-Nelson, A. and Goldsmith, P. (2016), 'Does 25 cents more per day make a difference? The impact of livestock transfer and development in rural Zambia', *Food Policy* **63**, 62–72.

Kapoor, M., Kelejian, H. H. and Prucha, I. R. (2007), 'Panel data models with spatially correlated error components', *Journal of Econometrics* **140**, 97–130.

Kelejian, H. H. and Prucha, I. R. (1998), 'A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances', *Journal of Real Estate Finance and Economics* **17**(1), 99–121.

Liu, X. and Lee, L. F. (2010), 'GMM estimation of social interaction models with centrality', *Journal of Econometrics* **159**(1), 99–115.

Manski, C. F. (1993), 'Identification of Endogenous Social Effects: The Reflection Problem', *The Review of Economic Studies* **60**(3), 531.

Miguel, E. and Kremer, M. (2004), 'Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities', *Econometrica* **72**(1), 159–217.

Moffitt, T. E., Caspi, A., Rutter, M. and Silva, P. A. (2001), Life-course persistent and adolescence-limited antisocial behaviour among males and females, *in* 'Sex Differences in Antisocial Behaviour', Vol. 13, pp. 207–226.

Munshi, K. (2004), 'Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution', *Journal of Development Economics* **73**(1), 185–213.

Mutl, J. and Pfaffermayr, M. (2010), The Hausman Test in a Cliff and Ord Panel Model, Technical report.

Nicholson, C. F., Mwangi, L., Staal, S. J. and Thornton, P. K. (2003), 'Dairy Cow Ownership and Child Nutritional Status in Kenya', *2003 AAEA Meetings Selected Paper* p. 30.

Paul Elhorst, J. (2014), Spatial panel models, *in* 'Handbook of Regional Science', pp. 1637–1652.

Randolph, T. F., Schelling, E., Grace, D., Nicholson, C. F., Leroy, J. L., Cole, D. C., Demment, M. W., Omore, A., Zinsstag, J. and Ruel, M. (2007), Role of livestock in human nutrition and health for poverty reduction in developing countries, *in* 'Journal of Animal Science', Vol. 85, pp. 2788–2800.

Rawlins, R., Pimkina, S., Barrett, C. B., Pedersen, S. and Wydick, B. (2014), 'Got milk? The impact of Heifer International's livestock donation programs in Rwanda on nutritional outcomes', *Food Policy* **44**, 202–213.

Ruel, M. T. (2003), 'Is dietary diversity an indicator of food security or dietary quality? A review of measurement issues and research needs', *Food and Nutrition Bulletin* **24**(2), 231–232.

Singh, I., Squire, L. and Strauss, J. (1986), 'Agricultural household models: a survey of recent findings and their implications', *The World Bank Economic Review* **1**(1), 149–179.

Toulis, P. and Kao, E. (2013), 'Estimation of Causal Peer Influence Effects', *Proceedings of The 30th International Conference on Machine Learning* **28**, 1489–1497.

Victora, C. G., Adair, L., Fall, C., Hallal, P. C., Martorell, R., Richter, L. and Sachdev, H. S. (2008), 'Maternal and child undernutrition: consequences for adult health and human capital', *The Lancet* **371**(9609), 340–357.

Whaley, S. E., Sigman, M., Neumann, C., Bwibo, N., Guthrie, D., Weiss, R. E., Alber, S. and Murphy, S. P. (2003), 'Animal Source Foods to Improve Micronutrient Nutrition and Human Function in Developing Countries', *J. Nutr* **133**, 3965–3971.