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Uninsured Health Shocks and Agricultural Productivity among Rural Households: The Mitigating Role of Micro-credit

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ABSTRACT *This article investigates how health shocks affect farm productivity in the presence of microcredit. It is expected that microcredit increases agricultural productivity by enhancing allocative and technical efficiency and by overcoming financial constraints that reduce purchase of inputs. However, microcredit will have competing uses in the event of uninsured health shocks to the household. Using an endogenous switching regression model and after accounting for self-selection, the results reveal that microcredit has a significant mitigating effect on farm productivity losses. Thus, microcredit generates a double dividend among smallholders serving as insurance against health shocks in rural areas and improving agricultural productivity.*

1. Introduction

In most developing countries, agriculture remains an important source of income to rural households (Davis et al., 2010). Yet, the productivity of agriculture depends largely on traditional farm technologies and land management practices that are labour intensive. Many small-holder farmers are severely constrained in enhancing the productivity of their land and remain trapped in poverty. One of the factors contributing to persistent poverty in poor rural households is health shocks affecting the household head or other members of the household. When health shocks occur, the amount of labour available for farming and other activities is diminished. Health shocks severely affect households' living standards by depleting the limited available productive resources, especially where households are unable to access formal insurance markets that would help insure against such shocks. Consequently, the resources that would otherwise be used for input purchase may be diverted to cope with health shocks.

Microfinance has been widely embraced by many developing countries as a means to mitigate the effects of shocks (Becchetti & Castriota, 2010) and smooth consumption (Islam & Maitra, 2012).[1] In addition, microfinance provides households with liquid capital to purchase inputs for farm production (Guirkinger & Boucher, 2008). Microcredit is expected to increase agricultural productivity by enhancing allocative and technical efficiency and by overcoming financial constraints that would reduce purchase of inputs. Microcredit may also permit a farmer to shift to a more remunerative crop mix (Morduch & Haley, 2002). However, funds obtained through microcredit have competing uses in

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households that are faced with both a health shock and a desire to increase productivity. If liquidity is a binding constraint, the amounts and combinations of inputs used by a farmer may deviate from optimal levels, reducing both production and consumption (Adeoti, 2010).

Many studies have explored the effect of microcredit on farm productivity in other parts of the developing world (Carter, 1989; Feder, Lau, Lin, & Luo, 1990; Foltz, 2004; Guirkinger & Boucher, 2008; Zeller, Diagne, & Mataya, 1998) but empirical evidence on this topic is lacking for most sub-Saharan African countries. Furthermore, existing studies do not account for the effect of uninsured health shocks on the relationship between credit and productivity. This study contributes to the existing literature on farm productivity by investigating how it is affected by health shocks and whether productivity loss can be mitigated by household use of microcredit.

The rest of the paper is organised as follows: Section 2 outlines the theoretical model. Section 3 describes the econometric model while Section 4 describes the choice and construction of explanatory variables. Discussion of the data is presented in Section 5 and the results are presented in Section 6. Section 7 concludes the paper with policy recommendations.

2. Theoretical model

A theoretical model is developed in this section to demonstrate the relationship between a health shock, credit and agricultural productivity. This model relies on the assumption that individuals are credit constrained and their participation in the credit market is limited as a result of either asymmetric information, lack of collateral, or risk aversion (Boucher, Carter, & Guirkinger., 2008; Islam & Maitra, 2012). Labour markets are imperfect in developing countries and, hence, family labour is important in carrying out farm activities. Consider a farm household endowed with land (K), a variable input bundle (N) and liquid assets (A).[2] Farm production is carried out by technology $F(N,K)$ that exhibits constant returns to scale in land and the variable input bundle$N$ (fertilisers, seeds, and so forth.). The quantity of land is fixed. Credit (d) can be used for purchase of the variable input bundle and as insurance against the cost of health shocks (H). Farm profits (Π) are obtained as

$$\Pi(n;K) = K[f(n) - pn] \tag{1}$$

where $n \equiv \frac{N}{K}$ represents the per hectare level of the variable input bundle, p is the per unit input price, the output price is normalised to one, and $f(n) \equiv F\left(\frac{N}{K}, 1\right)$ is the per hectare production function. The production function ($f(.)$) is increasing and strictly concave; hence, there is a unique profit maximizing level (n^*)of the variable input bundle that is independent of the household land endowment. The production possibilities of the farmer are categorised based on the use of microcredit and the occurrence of a health shock. For each household, there are four states: (1) no microcredit and a health shock, (2) no microcredit and no health shock, (3) microcredit and a health shock, and (4) microcredit and no health shock.

The optimal solution to the farmer's production problem, assuming there is no production risk, can be represented as the outcome of a profit maximisation problem (Bazaraa, Sherali, & Shetty, 1993). A farmer chooses n_i to solve

$$max_n f(n_i) - pn_i \tag{2}$$

subject to

$$pn_i \leq w_i$$

where w_i is wealth in four states ($i = 1, 2, 3, 4$).This framework enables us to explore the interplay between use of microcredit, health shocks and farm productivity. We are interested in determining if the maximum attainable net value of output per hectare in the presence of a health shock is altered by microcredit use.

In state 1, a farmer has wealth $w_1 = A - H$ and chooses n_1 implying that

$$n_1 = \frac{A - H}{p} \tag{3a}$$

In state 2, a farmer has wealth $w_2 = A$ and chooses n_2 implying that

$$n_2 = \frac{A}{p} \tag{3b}$$

In state 3, a farmer has wealth $w_3 = A + d - H$, chooses n_3 implying that

$$n_3 = \frac{A + d - H}{p} \tag{3c}$$

In state 4, a farmer has wealth $w_4 = A + d$ and chooses n_4 implying that

$$n_4 = \frac{A + d}{p} \tag{3d}$$

The concavity implied in technology assumption (4) is essential for the result obtained below, and a graphical representation of the technology is presented (see Figures 1–4 in the Online Appendix). That is, assume:

$$f(0) = 0, f'(.) > 0 \; and f''(.) < 0 \tag{4}$$

$$A + d > A + d - H > A > A - H > 0 \tag{5}$$

Case 1: If all constraints do not bind for all states i above, then solving the maximisation problem in Equation (2) gives

$$f'(n_i) > p \tag{6}$$

By assumption (4) and (5) and since state 4 is the least constrained while state 1 is the most constrained then:

$$f(n_4) > f(n_3) > f(n_2) > f(n_1) \tag{7}$$

Equation (7) implies Equation (8),

$$f(n_4) - f(n_3) \leq f(n_2) - f(n_1) \tag{8}$$

Case one systematically shows that when all the constraints do not bind for all states and given that some households are faced with an unanticipated health shock, then at the optimal point of input use, the difference in the level of output obtained by households with credit $\{(A + d - H/p)$ and $(A + d/p)\}$ is expected to be smaller than the difference in the level of output obtained by those with no credit $\{(A - H/p)$ and $(A/p)\}$. This implies that a drop in productivity is smaller when

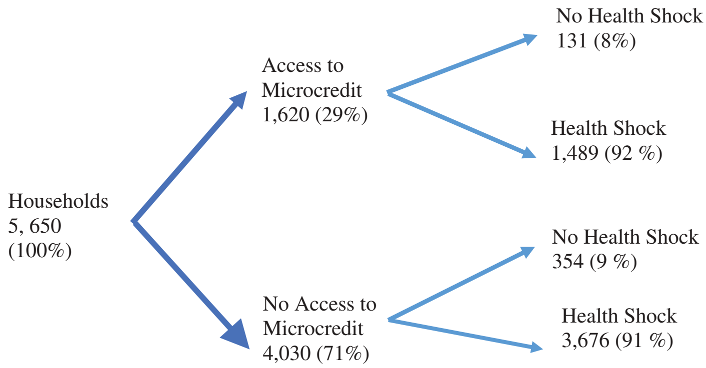

Figure 1. Composition of households surveyed given microcredit and health shocks status.

households have access to credit than when they have no access to credit if faced with a health shock (see illustration in Figure 1 in the Online Appendix).

Case 2: If the constraint for state 4 is binding but the constraints of the other states (3, 2, and 1) are not binding then at the optimal point:

$$f'\left(n_4^*\right) = p \leq f'(n_3) < f'(n_2) < f'(n_1) \tag{9}$$

Given assumptions in (4) and (5), Equation (9) implies

$$f\left(n_4^*\right) > f(n_3) > f(n_2) > f(n_1) \tag{10}$$

Hence,

$$f\left(n_4^*\right) - f(n_3) < f(n_2) - f(n_1) \tag{11}$$

Case two shows that if the constraint for state 4 is binding but the rest of the constraints do not bind and given that some households are faced with an unanticipated health shock, then at the optimal point of input use, the difference in the level of output obtained by households with credit $\{(A + d - H/p)$ and $(A + d/p)\}$ is expected to be smaller than the difference in the level of output obtained by those with no credit $\{(A - H/p)$ and $(A/p)\}$. This implies that a drop in productivity for households with credit is still smaller than the drop in productivity for households without credit when faced with a health shock (see illustration in Figure 2 in the Online Appendix).

Case 3: If state 3 and 4 constraints bind but state 1 and 2 constraints are not binding then at the optimal point:

$$f'\left(n_4^*\right) = f'\left(n_3^*\right) = p \leq f'(n_2) < f'(n_1) \tag{12}$$

implying that

$$f\left(n_4^*\right) = f\left(n_3^*\right) > f(n_2) > f(n_1) \tag{13}$$

Given assumptions in (4) and (5), Equation (13) implies,

$$f\left(n_4^*\right) - f\left(n_3^*\right) = 0 < f(n_2) - f(n_1) \tag{14}$$

Case three shows that if the constraint for state 4 and 3 are binding but the rest are nonbinding and given that some households are faced with an unanticipated health shock, then at the optimal point of input use, the difference in the level of output obtained by households with credit $\{(A + d - H/p)$ and $(A + d/p)\}$ is expected to be smaller than the difference in the level of output obtained by those with no credit $\{(A - H/p)$ and $(A/p)\}$. The drop in productivity for households with credit is still smaller than for households without credit when faced with a health shock (see illustration in Figure 3 in the Online Appendix).

Case 4: If states 2, 3, and 4 constraints bind but state 1 does not bind then at the optimal point:

$$f'(n_4^*) = f'(n_3^*) = f'(n_2^*) = p \le f'(n_1) \tag{15}$$

implying that

$$f(n_4^*) = f(n_3^*) = f(n_2^*) > f(n_1) \tag{16}$$

Given assumptions 4 and 5 Equation (16) implies (see Figure 4 for illustration)

$$f(n_4^*) - f(n_3^*) = 0 < f(n_2^*) - f(n_1) \tag{17}$$

Case four shows that if the constraint for state 4, 3, 2 are binding but constraint one does not bind and given that some households are faced with an unanticipated health shock, then at the optimal point of input use, the difference in the level of output obtained by households with credit $\{(A + d - H/p)$ and $(A + d/p)\}$ is expected to be smaller than the difference in the level of output obtained by those with no credit $\{(A - H/p)$ and $(A/p)\}$. All in all, the drop in productivity due to a health shock is still smaller for households that have access to credit relative to those that have no access to credit (see illustration in Figure 4 in the Online Appendix).

Case 5: If all constraints bind then;

$$f'(n_4^*) = f'(n_3^*) = f'(n_2^*) = f'(n_1^*) = p \tag{18}$$

implying that

$$f(n_4^*) = f(n_3^*) = f(n_2^*) = f(n_1^*) \tag{19}$$

Given assumptions 4 and 5 Equation (19) gives

$$f(n_4^*) - f(n_3^*) = 0 = f(n_2^*) - f(n_1^*) \tag{20}$$

Conclusion: For all possible n_i^*,

$$f(n_4) - f(n_3) \le f(n_2) - f(n_1) \tag{21}$$

The model shows that households that are subject to an unanticipated shock but either obtain microcredit or have access to microcredit experience a smaller reduction in farm productivity than households that do not have access to microcredit given at least one constraint does not bind. The provision of health insurance would eliminate output losses due to health shocks.

In summary, if households operate at the profit maximizing level of inputs per hectare without a health shock and the constraint is zero, then $f'(n) = p$. Access to microcredit has a neutralising effect on a negative health shock to the household, offsetting lost labour and minimising sale of assets and livestock that are used in farm productivity. This will result in a lower loss in productivity. In contrast, households faced with a negative health shock but with no access to credit bear the full impact of the shock and incur a higher loss in productivity. All in all, output per hectare is increasing in liquidity; therefore, the variable input bundle decreases in the face of uninsured health shocks or the absence of microcredit. The relationship between health shocks, credit, and agricultural output are tested using cross sectional data from Uganda.

3. Econometric model specification

Since microcredit access is not a random process, results of the effects of credit on agricultural productivity can be misleading if the issue of sample selection is not properly accounted for. In other words, it would be problematic to consider the producers without access to credit as a valid control group with the same characteristics as producers with access to credit. These two groups may potentially differ in many ways. The potential differences include observable characteristics such as land, wealth and education, and unobservable characteristics such as farming and managerial skills, abilities, genetic makeup, motivations, and risk attitudes, among others. Given potential differences between credit and non-credit producers, there are two possible explanations for the association between credit and farm productivity: i) there may be a true productivity enhancing effect of credit despite the observed and unobserved differences, or ii) there may be a spurious correlation induced by the fact that credit recipients are better farmers than non-credit recipients and so would exhibit observed higher productivity even in the absence of credit.

We circumvent the sample selection issue by controlling for both observable and unobservable characteristics of farmers. We do so, relying on an endogenous switching regression model (Ali, Deininger, & Duponchel, 2014; Maddala, 1983). Practically, the analysis consists of joint estimation of the probability of having access to credit and the output level given that a household faces a health shock. Some of the variables that determine whether households are credit constrained also influence production and consumption decisions (Sadoulet & De Janvry, 1995).[3]

The process by which households are selected into either the credit or no credit state is modelled as a linear function of observed factors affecting demand for and supply of credit. This relationship can be specified as follows:

$$d_i^* = \delta' Z_i + \eta_i \tag{22}$$

$$d_i = \begin{cases} 1 \ \mathit{if} \ d_i^* > 0 \\ 0 \ \mathit{if} \ d_i^* \leq 0 \end{cases} \tag{23}$$

where d_i^* is a continuous variable that represents a latent propensity of a household i to be credit constrained (no access to credit) or unconstrained. The variable Z_i is a vector of factors affecting credit supply and demand and η_i is an error term with mean zero and variance σ_η^2. In Equation (23), d_i is a binary variable that takes the value of one if d_i^* exceeds zero and corresponds to household i having access to credit either in the formal or informal market and zero otherwise.

Farm productivity, given that a household has access or no access to credit in the face of a health shock, is modelled as follows:

$$\text{Regime 1}: y_{1i} = \beta_1 X_{1i} + \gamma_1 A_{1i} + \varphi_1 H + \alpha_1 IMR_1 + \varepsilon_{1i} \ \text{if} \ d_i = 1 \tag{24}$$

$$\text{Regime 2}: y_{2i} = \beta_2 X_{2i} + \gamma_2 A_{2i} + \varphi_2 H + \alpha_2 IMR_2 + \varepsilon_{2i} \ \text{if} \ d_i = 0 \tag{25}$$

where in Equation (24) and (25), y_{1i} is farm productivity with access to credit and y_{2i} is farm productivity without access to credit. This is the dependent variable, measured as the natural log of output per hectare. The variable X_i is a vector of observed factors that are hypothesised to explain productivity (for example, educational level, farming experience, extension visits and so forth, see Table 1), A_i is a vector of farm capital (for example, oxen used for ploughing), H is an exogenous health shock, and IMR is the Inverse Mills Ratio. The parameters, β_1, β_2, γ_1, and γ_2 capture the effects of the covariates on farm productivity and φ_1 and φ_2 are the key parameters of interest representing the effects of health shocks on agricultural productivity with and without access to microcredit. The theoretical model predicts that $\varphi_2 < \varphi_1 < 0$.

The error terms in Equation (22), (24) and (25) are η_i, ε_{1i} and ε_{2i}, respectively with mean vector zero and covariant matrix Σ.

That is,

$$(\eta, \varepsilon_1, \varepsilon_2) \sim N(0, \Sigma), with\ \Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1\eta} \\ \sigma_{12} & \sigma_2^2 & \sigma_{2\eta} \\ \sigma_{1\eta} & \sigma_{2\eta} & 1 \end{bmatrix},$$

where σ_η^2 is the variance of the error term in the selection Equation (22) and has been set to one because by the nature of conditions (24) and (25) δ is estimable only up to a scale factor. The variances σ_1^2 and σ_2^2 are from the error terms in the farm productivity functions (24) and (25). The symbol, $\sigma_{1\eta}$,

Table 1. Descriptive statistics to compare the characteristics of households with and without health shocks

Variables	All (N = 5646)	Health shock N = 5164, 91%)	No health shock (N = 484, 9%)	T-Statistics
Age of head (years)	43.74	43.70	44.20	0.67
	(15.65)	(15.59)	(16.25)	
Educ. of head (years)	5.71	5.69	5.98	1.66
	(4.05)	(4.03)	(4.33)	
Household size	6.02	6.39	5.86	−5.82
	(3.08)	(3.05)	(3.08)	
Number of adults	3.00	3.04	2.60	−5.33
	(1.73)	(1.73)	(1.65)	
Dependents	3.15	3.22	2.30	−10.05
	(1.95)	(1.95)	(1.73)	
Sex of head	0.74	0.74	0.73	−0.68
	(0.44)	(0.45)	(0.45)	
Farm size (ha)	3.09	3.12	2.69	−3.17
	(2.85)	(2.85)	(2.75)	
Value of inputs (‘000)	31.73	33.38	14.10	−0.48
	(847.74)	(886.36)	(63.33)	
Value of productive assets	698.52	674.78	951.76	1.64
	(3545.40)	(3205.81)	(6085.46)	
Value of other savings	104.36	106.09	85.89	−1.56
	(272.67)	(275.54)	(239.44)	
Own mobile phone	0.12	0.12	0.13	0.72
	(0.33)	(0.32)	(0.34)	
Visited by extension agent	0.07	0.08	0.06	−1.45
	(0.26)	(0.26)	(0.23)	
Credit	0.29	0.29	0.27	−0.82
	(0.45)	(0.45)	(0.44)	

Notes: Standard deviations are in parentheses.

represents the covariance of η_i andε_{1i}, and $\sigma_{2\eta}$ is the covariance of η_i and ε_{2i}. The farm productivity variables, y_{1i} and y_{2i}, are not observed simultaneously.

Since the error term of the selection Equation (22) is correlated with the error terms of the productivity functions (24) and (25), the expected values of ε_{1i} and ε_{2i}, conditional on sample selection, are nonzero and are defined below as:

$$E[\varepsilon_{1i}|d_i = 1] = \sigma_{1\eta}\frac{\phi(Z_i\delta')}{\Phi(Z_i\delta')} = \sigma_{1\eta}\lambda_{1i} \tag{26}$$

$$E[\varepsilon_{2i}|d_i = 0] = -\sigma_{2\eta}\frac{\phi(Z_i\delta')}{1-\Phi(Z_i\delta')} = -\sigma_{2\eta}\lambda_{2i,} \tag{27}$$

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density and normal cumulative density functions, respectively. If the parameters $\sigma_{1\eta}$ and $\sigma_{12\eta}$, respectively for the IMRs λ_{1i} and λ_{2i}, are statistically significant, then access to microcredit and farm productivity are correlated. The robustness of the model lies in its ability to provide consistent parameter estimates whether there is sample selection (that is, $\sigma_{1\eta}$ and/or $\sigma_{12\eta}$ significantly different from zero) or not.

3.1. Estimation strategy for endogenous switching model

We estimate the selection equation and two productivity equations specified above by maximum likelihood, which is more efficient than Heckman's two-step estimator. The dependent variable in the selection equation is a dummy variable that takes the value of one if the household had access to microcredit in the last year and zero otherwise. There are various reasons why households do not have access to microcredit: lack of creditworthiness; lack of collateral, transactions costs, moral hazard or adverse selection (Boucher et al., 2008). In many cases, a number of market imperfections combine to drive farmers out of the microcredit market.

4. Choice and construction of the explanatory variables

4.1. Health shocks

Previous studies indicate that the measurement of the health shock variables is important in analysing the impact of said shocks on outcome variables (Cochrane, 1991). In this paper, we use self-reported health shocks based on a household survey; the health shock questions were asked to all household members aged 15 and older while the mother/guardian answered for children less than 15 years. Schultz and Tansel (1997) recommend use of self-reported functional activity as a better indicator of health status. The respondents were asked the following question: for how many days did you have to stop doing your usual activities due to illness during the past 30 days and six months? We use the six month period since a typical agricultural season lasts about half a year in the study area. The health shock variable is included as both a continuous explanatory variable and as a categorical variable in the OLS and switching regression models. When the health shock is included as a continuous variable, it is measured as the number of days a household member did not work due to illness plus the number of days a member had to refrain from work or income earning activities if any other member in the household was sick in the last 180 days. Health shocks are expected to have a negative effect on productivity.

The health shocks are grouped into exogenous unanticipated illnesses such as acute diarrhoea, major weight loss, acute fever, skin rash, severe headache, fainting, vomiting, coughing blood, pain on passing urine, genital sores, abdominal pain, sore throat, difficulty breathing, burns, and fractures.

Non-exogenous health shocks that the household would have anticipated and, hence, internalised include chronic diarrhoea (one month or more), recurring fever, chronic joint disease, spinal lesion, surgical operation, child birth related, HIV/AIDS, and other long term illnesses. These anticipated health shocks were not included in the analysis. The average cost of treatment for non-persistent, unpredictable and idiosyncratic illnesses such as malaria in Uganda is between US$2 and US$25 Nabyonga-Orem, Nanyunja, Marchal, Criel, & Ssengooba, 2014).

4.2. Credit

Credit in Uganda can be accessed from several sources: formal financial institutions such as regulated commercial banks; microfinance institutions (MFIs); savings and credit cooperatives (SACCOs); non-governmental organisations; and informal sources such as friends and relatives, local money lenders, shop keepers, landlord/employer, village level associations (rotating savings). SACCOs are member-based financial institutions serving mostly rural areas; they have gained a lot of applause from the government. SACCO members agree to save their money and provide loans to members at a reasonable rate (Kabuga & Batarinyebwa, 1995). The most recent data from the 2011 SACCO census shows that there were approximately 2094 SACCO branches representing 1.3 branches per every 10,000 adult Ugandans.

The MFIs, loan schemes and SACCOS use different lending technologies to serve their clients. These include individual-based lending in which there are only one or two guarantors per loan. Collateral in form of land title or crops grown in a field is also a requirement to obtain this kind of loan (Xavier & Karlan, 2009). Another mechanism used is joint-liability group lending whereby group members cross-guarantee each other's loans without the need for physical collateral. A census study conducted in 2006 showed that 37 per cent of these institutions rely only on individual lending, 57 per cent use both individual and group lending approaches, and 6 per cent use only group lending (Karlan, 2007). SACCO borrowers also use their shares of membership as collateral to access loans (Nuwagaba, 2012).

Some of the services offered by the MFIs and loan schemes include credit to finance trade activities, individual business loans for non-agricultural investments, agricultural loans, and consumer loans. Loans by SACCOs include agricultural loans to cover expenses such as cow fattening, fertilisers, sprayers and improved seeds, crop growing, fencing of farm land, dam construction and livestock rearing, and asset loans intended to acquire capital assets such as tractors, ox ploughs and milking machines (Nuwagaba, 2012). The loan period often varies from 6–36 months with an average loan size of $60 for individual loans and $453 for group credit (Obara, 2009). According to Goodwin-Groen, Bruett, and Latortue (2004) about 1500 MFIs were serving more than 935,000 small savers and close to 400,000 borrowers in the country.

4.3. Farm size

Farm size is measured as amount of land cultivated under crop. Udry (1996) finds that output per hectare is strongly declining with the size of the plot. The inverse plot size-yield relationship has been observed in other African datasets. Other empirical studies confirm the negative relationship between farm size and output per hectare (Lipton, 2010). Explanations often cited for this negative relationship include either a failure to properly measure key factors such as land quality or area, or small farmers' application of more than the optimum amounts of certain inputs due to imperfections in markets for key factors such as labour, land, and insurance. We therefore control for farm size in our estimations.

Other covariates included in both the productivity and selection equations are drawn from literature on credit and productivity (Feder et al., 1990; Fletschner, Guirkinger, & Boucher, 2010; Guirkinger & Boucher, 2008). These explanatory variables include purchased inputs (inorganic fertilisers, manure, improved seed, and pesticides), value of assets (livestock), household characteristics (age, education, and gender of household head, number of adults in the household, dependency ratio and exposure to extension services), regional dummies, and health shocks. The value of purchased inputs is included to control for differences in input requirements and expenditures across households. It is expected to affect productivity positively. The value of assets such as livestock is included to control for initial capital available that may affect productivity. It is expected to be positive since productive assets increases agricultural output. A study by Latruffe (2005) in Poland finds that farmers with more tangible assets were less constrained than those without. Other studies have also shown that owned assets play a significant role in both productivity and ability to borrow (see Benjamin & Phimister, 2002; Briggeman, Towe, & More Hart, 2009). Age and education of household head are included to account for experience and knowledge level of the head of the household. The household head's education level is expected to have a positive influence on productivity since more education likely implies knowledge of efficient allocation of scarce resources. Gender is included to account for different resource endowments among gender types. Men tend to be more endowed with land and other resources while women may not have the means to obtain credit due to resource constraints (Udry, Haddinott, Alderman, & Haddad, 1995). Participation in extension activities is included as a dummy variable to capture technical advice provided by extension agents. Regional dummy variables are included to account for differences in agro-ecological zones due to differential resource endowments and farming conditions as well as borrowing potential.

4.4. Exclusion restriction for identification

As discussed above, credit access is likely a source of sample selection. The econometric remedy of sample selection requires the identification of variables as exclusion restrictions. In our case, these would be variables that explain credit access but not agricultural productivity directly. We rely on two exclusion restriction variables to account for potential selection bias. The first variable measures the proportion of neighbours who are borrowers in the community. A higher fraction of neighbours with access to credit markets is anticipated to relax credit constraints as it likely reduces both the transaction costs associated with credit application and the uncertainty resulting from an incomplete understanding of credit lending conditions. A threat to the exogeneity of the exclusion restriction is potential spatial correlation in agricultural productivity. Spatial correlation in yields can be spurred by information sharing and technology transfer among neighbours; it is also possible that microcredit institutions may prefer to offer loans in more productive areas. If so, the variable is likely to be directly correlated with agricultural productivity. To guard against such a possibility, we include 56 district-level dummies in our regression to control for district (neighbourhood) fixed effects that create spatial correlation in productivity within districts.

The second exclusion restriction variable is a dummy indicating whether a member of the household has a savings account. Opening a savings account is a requirement for applying for a loan by many microfinance and formal institutions. A savings account also allows households to develop good financial history that would enable them to access different financial products. On the other hand, the mere fact of having a savings account should not have any direct impact on agricultural productivity once the value of household savings is accounted for. Most rural households tend to save in the form of other easily liquidable assets such as poultry and small ruminants that are already included in the empirical model.

5. Data sources and descriptive statistics

This study utilises data from the Uganda National Household Survey (UNHS) collected by the Uganda Bureau of Statistics (UBOS). The UNHS 2005/06 survey was undertaken from May 2005 to April 2006 and covered 5650 farm households sampled countrywide. The survey has five modules: socio-economic, agriculture, community, market, and qualitative modules. A two-stage sampling design was used to draw the sample. At the first stage, enumeration areas (EAs) were drawn with probability proportional to size (PPS) and, at a second stage, households were selected. A stratum representing persons in internally displaced people (IDPs) camps was selected separately and an additional sample of 30 EAs was drawn in those areas. A total of 783 EAs representing both the general household population and the displaced subpopulation was selected for the UNHS 2005/2006. The household and agricultural questionnaires collected information that includes socioeconomic characteristics, health status and health shocks, farm output in physical and value terms, input usage, access to microcredit, and other variables. The size of the sample available for analysis is 5650 farm households. Figure 1 shows the composition of households with and without microcredit and with and without health shocks. Out of the total sample, 29 per cent of households had access to microcredit while 71 per cent lacked access to credit. A high proportion (90%) of all sampled households reported having had one or more household members sick during the preceding six months. However, there is a wide range in the number of work days lost to illness.[2]

Summary statistics for selected attributes of the sample are presented in Table 1 for households with a health shock and those without a health shock. As can be seen from the descriptive statistics table, household that are larger in size experience health shocks with a higher frequency as evidenced by the significant differences between the means of household size, number of adults and dependents. This is expected since larger households have a higher probability of having at least one person experience a health shock. Besides these variables, only farm size and education of the household head are statistically significant. The fact that households with educated heads experience slightly fewer short-term health shocks may be because educated heads are more likely to take precautions against certain diseases such as diarrhoea, for example. The significance of farm size may be due to a high correlation between farm size and household size (larger households generally have more land) and to effects of more work days on a larger field. Other than education and size (household size and farm size), none of the remaining covariates exhibits a statistically significant coefficient for the difference of means test, suggesting that households with and without health shocks are quite balanced on average, size effects aside.

6. Estimation results and discussion

6.1. OLS results

The results of the OLS estimation are presented in Table 1 in the Online Appendix. Column (1) in the table shows estimates when the health shock is introduced in the model as three dummy variables. These include when the health shock in days is less than 10 (the reference point), between 10 and 30 days and when days ill are greater than 30. Column (2) in the table shows the results when the health shock is introduced in the model as a continuous variable measured as the average number of days household members were sick. The coefficients for the health shock in column (1) reveal that there is a statistically significant loss in productivity of households that experienced a health shock of greater than nine days. The estimate in column (2) for health shock also shows that health shocks significantly reduce productivity. However, these results do not account for self-selection; hence, the estimates are inconsistent.

6.2. Results of the selection equation

The results of the selection Equation (22) are displayed in Table 2. They show that the coefficients on the two exclusion restrictions are positive and significant as expected. F-tests reveal that the exclusion restrictions used are relevant in explaining credit access. Results for other exogenous variables show that education of household head, the value of purchased inputs, value of other savings and productive assets have a positive and significant effect on the likelihood of credit access. In contrast, age increases the odds of being credit constrained. Households that live in eastern and western regions of Uganda have a higher probability of credit access than those households that live in northern Uganda (reference region). This could be because the northern part of the country had a long spell of civil war that disrupted MFI activity in the region.

Table 2. Maximum likelihood estimates of the switching regression model when health shock is used as dummy and credit is used as access

Variables	Credit constrained	Credit unconstrained	Selection equation
Health shock (=1 if sick between 10–30 days, 0 otherwise)	−0.21***	−0.06**	
	(0.06)	(0.03)	
Health shock (=1 if sick over 30 days, 0 otherwise)	−0.37***	−0.12	
	(0.12)	(0.08)	
Gender (=1 if male, 0 if female)	0.04	0.09**	−0.0001
	(0.07)	(0.04)	(0.05)
Age of head (ln)	0.65***	0.27***	−0.64***
	(0.15)	(0.06)	(0.06)
Dependency ratio	0.004	−0.01	0.044*
	(0.03)	(0.02)	(0.02)
Education of head (ln)	0.02	0.09***	0.14***
	(0.05)	(0.02)	(0.03)
Farm size (ln)	−0.47***	−0.49***	0.01
	(0.04)	(0.02)	(0.02)
Value of purchased inputs (ln)	0.02***	0.05***	0.01**
	(0.01)	(0.004)	(0.01)
Value of productive assets (ln)	0.06***	0.09***	0.07***
	(0.02)	(0.01)	(0.01)
Value of other savings (ln)	0.02***	0.03***	0.02***
	(0.01)	(0.003)	(0.004)
Own mobile phone (dummy)	0.02	0.01	0.05
	(0.14)	(0.05)	(0.08)
Visited by extension (dummy)	0.14	0.18***	0.16*
	(0.16)	(0.06)	(0.09)
Central region (dummy)	0.61	0.56	0.21
	(0.58)	(0.46)	(0.56)
Eastern region (dummy)	−1.06	−0.12	2.10***
	(0.76)	(0.44)	(0.51)
Western region (dummy)	−1.04**	0.59	1.66***
	(0.49)	(0.43)	(0.41)
Proportion of neighbours			0.11**
			(0.05)
Savings account (dummy)			0.34***
			(0.08)
Constant	7.38***	9.63***	0.59
	(0.75)	(0.45)	(0.42)
District dummies	YES	YES	YES
$Sigma_i$	1.30***	0.90***	
	(0.15)	(0.03)	
Rho_i (i = 1,2)	−0.77***	−0.30	
	(0.09)	(0.172)	
Likelihood Ratio (LR) test of independent equations:chi2(2) = 26.78 Prob > chi2 = 0.000			
F-value 12.36			
Observations	5,630	5,630	5,630

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels, respectively. Robust standard errors are in parentheses.

6.3. Results of the productivity equations

Table 2 presents the results of the endogenous switching regression model (Equations 24 and 25) for credit constrained and credit unconstrained households.[4]

The coefficients on the first health dummy variable is statistically significant for both households with and without credit access. However, the size of the coefficient for credit constrained households is much larger (−0.2), indicating that a health shock of 10 to 30 days leads to a 20 per cent productivity loss of credit-constrained households, compared to a 6.0 per cent productivity loss for credit unconstrained households. Likewise, the coefficient on the second health shock dummy (sick over 30 days) is large and significant for credit constrained households (illness leads to a 37% decline in productivity) but is not significant for credit unconstrained households. These differences are statistically significant.[5] In general, the results on the health dummies align with the theory and can be explained by the fact that households that have access to credit are able to mitigate the effects of illness on productivity by getting medical care or hiring labour to substitute for the labour that would have been provided by the sick household members. Households without credit suffer a larger direct loss of productivity because they may have to rely on a reduced labour force and may have to sell productive assets such as bullocks used for ploughing to cater for immediate health shocks. Most rural dwellers in Uganda and many other developing countries have no public or private medical insurance, and health care providers generally do not provide treatment until the patient pays for it. In Uganda, only select individual employers provide health insurance to their employees. No such provision is in existence for informal workers or those in rural farming communities (Kagumire Asare et al., 2004). These uninsured households have to pay out-of-pocket for their health expenses which greatly affects their ability to invest in farming and other activities. Findings by Leive and Xu (2008) show that households in several African countries with no health insurance provision often cope with health shocks by either selling assets or borrowing. Our findings here are in line with those by Islam and Maitra (2012) who find that households that have access to microcredit in Bangladesh do not need to sell livestock when faced with a health shock in order to insure consumption. In a related vein, a study by DeLoach and Lamanna (2011) that measures the impact of microfinance on child health outcomes in Indonesia finds that the presence of microfinance institutions in communities significantly improves the health of children.

For the remaining control variables in the productivity equations, the age of household head, the value of purchased inputs, the value of productive assets, and the value of savings have a positive and significant effect on productivity of both credit constrained and credit unconstrained households. Gender of household head, education of household head and visitation by an extension worker have a positive and significant effect on productivity only of credit unconstrained households. However, the differences between these coefficients by credit status are not statistically significant.

Farm size has a similar negative and statistically significant effect on productivity of both credit constrained and unconstrained households. A negative relationship between farm size and productivity has been reported in a number of African studies (Ali et al., 2014; Udry, 1996; Udry et al., 1995). These studies associate this effect with resource use inefficiency, particularly among labour constrained households.

The likelihood ratio test for joint independence of the three equations is rejected at the 1 per cent level. This test reveals that the hypothesis that the microcredit selection equation and productivity equations are independent is rejected.

To summarise, the results indicate that uninsured health shocks have a large and negative impact on the productivity of Ugandan farm households. Households that are credit unconstrained are able to manage the shock better; the loss in productivity following a health shock for households that use credit is significantly smaller than for those that do not. Health shocks are an important determinant of farm productivity in the absence of health insurance, and participation in credit programmes reduces their negative effect.

6.4. Health shock measured as a continuous variable

We re-estimated the model but using a continuous measure of heath shocks: the log of the number of sick days instead of the sick dummies. The results in Table 3 show that the coefficient on the health shock variable is statistically significant for both household types. However, the magnitude of the coefficient for credit constrained households is again much larger than for credit unconstrained households. Specifically, we find that a one day increase in number of days not worked due to illness

Table 3. Maximum likelihood estimates of the switching regression model when health shock is used as continuous variable and credit is used as access

Variables	Credit constrained	Credit unconstrained	Selection equation
Health shock (ln days not worked)	−0.07***	−0.03**	
	(0.02)	(0.01)	
Gender (=1 if male, 0 if female)	0.04	0.09**	−0.001
	(0.07)	(0.04)	(0.05)
Age of head (ln)	0.64***	0.26***	−0.64***
	(0.15)	(0.06)	(0.06)
Dependency ratio	0.01	−0.01	0.05*
	(0.03)	(0.02)	(0.02)
Education of head	0.02	0.09***	0.14***
	(0.05)	(0.02)	(0.03)
Farm size (ln)	−0.47***	−0.45***	0.01
	(0.04)	(0.02)	(0.02)
Value of purchased inputs/ha (ln)	0.02***	0.05***	0.01**
	(0.01)	(0.004)	(0.005)
Value of productive assets (ln)	0.06***	0.09***	0.07***
	(0.02)	(0.01)	(0.01)
Value of other savings (ln)	0.023***	0.03***	0.02***
	(0.01)	(0.003)	(0.004)
Own mobile phone (dummy)	0.03	0.01	0.05
	(0.15)	(0.05)	(0.08)
Visited by extension (dummy)	0.14	0.18***	0.16*
	(0.16)	(0.06)	(0.09)
Central region (dummy)	0.67	0.56	0.21
	(0.57)	(0.46)	(0.55)
Eastern region (dummy)	−1.00	−0.12	2.09***
	(0.82)	(0.44)	(0.51)
Western region (dummy)	−1.03**	0.53	1.65***
	(0.50)	(0.44)	(0.41)
		(0.19)	(0.41)
Proportion of neighbours			0.12**
			(0.05)
Savings account (dummy)			0.34***
			(0.08)
Constant	7.36***	9.67***	0.58
	(0.76)	(0.45)	(0.42)
District dummies	YES	YES	YES
$Sigma_i$	1.35***	0.91***	
	(0.15)	(0.91)	
Rho_i ($i = 1,2$)	−0.79***	−0.33**	
	(0.15)	(0.16)	
Likelihood Ratio (LR) test of independent equations: chi2 (2) = 31.40 Prob > chi2 = 0.000			
F- value 12.36			
Observations	5,630	5,630	5,630

Notes: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels, respectively. Standard errors are in parentheses. The health variable here was obtained from the questionnaire question: For how many days in total did you have to stop doing your usual activity due to illness during the past six months (including the past 30 days)? And for how many days did you have to stop doing your usual activities caring for other member of the household who were sick during the past six months?

(an 11% increase given the sample average number of sick days of 8.44) leads to a 0.7 per cent loss in productivity for credit constrained households and roughly a 0.3 per cent loss in productivity for credit unconstrained households. Overall, the results conform to the earlier results when health shock was measured with three dummy variables.

6.5. Robustness check

To test for robustness, the selection equation was re-estimated using an alternative credit variable. Instead of access to credit, this variable was used as 'actually borrowed'. The health shock variable was included first as a categorical variable and then as a continuous variable. The results were then compared to check for the robustness of the model (Tables 2 and 3 in the Online Appendix). We found that the coefficient on the health shock in Tables 2 and 3 is negative for both credit constrained and credit unconstrained households. However, the coefficient on the health shock is statistically significant for credit constrained households but is not significant for credit unconstrained households. This shows that having access to microcredit alone does not guarantee that the effects of health shocks are mitigated. In contrast, households that actually obtained microcredit were able to cope with health shocks without a significant loss in productivity. These results confirm the hypothesis that uninsured health shocks have adverse effects on productivity and microcredit access may be able to mitigate the shock but households are better off when they actually obtain the microcredit.

7. Conclusions

This article investigates how health shocks constrain productivity and the mitigating role of microcredit. As a first step, a simple theoretical framework is developed that explores the relationship between productivity, health shocks and credit. If no constraint binds and households do not face an uninsured health shock, they operate at the profit maximizing level of inputs per hectare. However, if households are faced with uninsured health shocks as is the case in most developing countries, resources that would have been used for purchase of inputs are diverted to cope with the shock. The model illustrates that credit has a neutralising effect on health shocks to the household.

The empirical analysis is based on a national household dataset from Uganda. Empirical estimates from the endogenous switching regression model show that credit access significantly mitigates the impact of uninsured health shocks on agricultural productivity. The loss in productivity experienced by credit constrained households is larger regardless of the duration of the health shock.

Taken together, these findings have important policy implications. First, there is a crucial need for governments to speed up the process of formation of health insurance schemes that are inclusive and affordable. This will ensure that low income rural households are able to access and utilise medical care as needed. Based on this research as well as other empirical studies reviewed above, increased access to reliable healthcare by farmers should significantly curtail agricultural productivity losses due to health issues. Second, policies and programmes that lead to creation of strong and sustainable farmers' organisations will spur the creation of famer groups, which in turn facilitates access to credit by removing the need for hefty physical collateral. Third, there is a need to invest in infrastructure so that credit lending institutions are able to reach rural farmers, many of whom do not have no access to credit.

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The data, code and additional material will be available on request to anyone interested and the appendix will be available online.

Disclosure statement

No potential conflict of interest was reported by the author.

Notes

1. Microfinance is wider than microcredit but the two terms are used interchangeably in this article.
2. Variable input bundle include seeds, fertilisers and labour while *A* is not a factor of production but refers to assets that can easily be made liquid.
3. 'Credit constrained' is used to refer to households that did not obtain credit for various reasons such has high interest rates, lack of collateral or unavailability of lenders. 'Credit unconstrained' is used to refer to households that obtained credit or did not obtain credit because they had sufficient funds; hence, had no need to borrow.
4. Estimation was carried out with Stata using the 'movestay' command programmed by Lokshin and Sajaia (2004).
5. Following Clogg, Petkova, and Haritou (1995), we calculated the asymptotically standard normal z statistic = $(\beta_1 - \beta_2)/(\text{var}(\beta_1) + \text{var}(\beta_2))^{1/2}$ to test if the effects of health shocks are the same across credit status. Doing so, we find that null hypothesis that the coefficients are the same can be rejected at the 5 and 10 per cent significance levels, respectively for the first and second health dummies.

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