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Pia Nilsson

ABSTRACT

This paper tests for external effects of local economic activity on non-farm income using survey data from Rwanda. The empirical analysis uses a random sample of 8071 households and a multilevel model to mitigate correlations between individual outcomes and geographical variables. Findings show a positive association between a higher initial local diversity of economic activity and non-farm earnings. Results also point to the importance of access to markets and services indicating that an important part of a household's capacity to earn non-farm income is associated with factors that are external to the household.

KEYWORDS

Rwanda; non-farm; spatial spillovers; industry diversity; multilevel

JEL O12, R12, R20

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INTRODUCTION

The non-farm sector plays an important role in the rural economy in developing countries and is expanding in many parts of Africa in terms of income and employment (Bigsten, 1983; Ellis, 2000; Davis, Di Giuseppe, & Zezza, 2014). The limited supply of arable land, declines in agricultural production, rapid population growth and a rising share of the working-age population are factors that have contributed to making non-farm growth an important part of economic development (Lanjouw & Lanjouw, 2001). Several benefits can be associated with the expansion of non-farm economic activities. Non-farm income can assist rural households and farms to smooth income and consumption and provide insurance for external shocks related to rapidly changing external conditions, such as droughts and erosion (Reardon, Taylor, Stamoulis, Lanjouw, & Balisacan, 2000).[1] The opportunity to earn non-farm income also has the potential to improve food security, particularly among households that lack access to land and the assets needed to turn agriculture into a productive source of income (Barrett, Reardon, & Webb, 2001). The growth of the non-farm sector also plays a key role in a wider process of structural change, which is transforming many developing countries, including Rwanda, from agricultural to service-oriented economies (Uwitonze & Heshmati, 2016). Even though the average share of non-farm income is increasing over time, there are several constraints facing rural households and farms that attempt to participate in non-farm activities. These include lack of capital, education, information and market access. There is evidence that the share of non-farm activities is among the lowest in Rwanda compared with other sub-Saharan countries (André & Platteau, 1998; Dabalen, Paternostro, & Pierre, 2004).

There is a large literature on the determinants of non-farm income in the context of sub-Saharan Africa. Yet, most studies have focused on the characteristics of the households and firms. For instance, the importance of various push and pull factors, such as human capital, access to credit and productive assets in explaining participation in non-farm activities (Barrett et al., 2001; Bigsten & Tengstam, 2011; Ellis, 2000; Rijkers & Söderbom, 2013). Much less attention has been given to the role of location-specific factors, including the benefits of being close to a diverse set of economic actors to reduce transactions costs and gain from spillover effects from shared knowledge (Ali & Peerlings, 2011). Studies that address these factors in the context of rural Africa also tend to focus on firm performance and the benefits associated with the clustering of non-farm microenterprises in urban

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areas (e.g., Owoo & Naudé, 2017; Rijkers, Söderbom, & Loening, 2010).

This paper contributes to the literature by focusing on external effects of local economic activity on per capita non-farm income among rural households and farms. Rural households and farms that ground their income on agricultural activities account for a clear majority of economic activity across developing countries, making this an important focus. Rwanda is no exception as more than 80% of the population lives in rural areas combining small-scale food cropping and livestock rearing with a diverse set of agricultural and non-agricultural activities (Abdulai & CroleRees, 2001). This paper argues that the possibilities of rural households to earn non-farm income should be linked to knowledge and information spillovers and opportunities offered by other economic activities and the market chances that arise in the surrounding geography (Jalan & Ravallion, 2002). Considering the growing importance of the service sector to the Rwandan economy and the argument that knowledge spillovers in rural areas are more prominently linked to services (Goffette-Nagot & Schmitt, 1999), the analysis also examines the role played by spillovers that are associated with the clustering of services on per capita non-farm incomes.

The empirical analysis uses detailed household-level data and geographical data obtained from two rounds of the Comprehensive Food Security and Vulnerability Analysis (CFSVA) survey, conducted in 2006 and 2009. The analysis is carried out by controlling for spatial autocorrelation in the data by considering different levels of geographical disaggregation and employing a multilevel model. Using this approach, unobserved spatial heterogeneity is modelled by allowing for serial correlation among the higher geographical levels to mitigate correlations between individual outcomes and geographical variables.

The paper is organized as follows. The next section presents background information and reviews the most relevant literature linking spatial spillovers to non-farm growth in the context of rural areas. The third section describes and summarizes the data and the estimated model. The fourth section present the results and discusses their relevance in relation to theory and the prior literature. The fifth section concludes by discussing the implications of the results for policies aimed at spurring non-farm growth in Rwanda.

BACKGROUND AND MOTIVATION

The idea that clustering of economic activities enables firms to engage in different forms of interaction, which spurs additional activities, has received growing attention in the context of developing countries (Jalan & Ravallion, 2002; Owoo & Naudé, 2017; Ravallion & Chen, 2007; Rijkers et al., 2010). This is based on the fact that there are externalities through knowledge and information flows as firms can learn from each other via networks and knowledge spillover effects, which stimulate innovation and growth (Lucas, 1993; Romer, 1986). Such spillovers are thought to transmit via physical interactions between economic actors and they highlight the importance of geographical proximity and face-to-face contacts (Storper & Venables, 2004).[2]

Although there is an agreement that locational factors play a key role in economic development, there are different views about which types are important and in which context they matter (Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Henderson, Kuncoro, & Turner, 1995). The benefits associated with the spatial concentration of economic activity within a given industry are commonly denoted as localization economies, whereas the economies of scale resulting from the concentration of economic activity, irrespective of its industrial composition, are denoted as urbanization economies (Rosenthal & Strange, 2004). Agglomeration and urbanization economies may seem relevant only in an urban context as there are dependencies between rural and urban regions where the theories of agglomeration economies clearly favour the latter (McCann & Ortega-Argilés, 2015). However, there are dependencies between and within rural regions, which also makes it relevant to discuss the benefits of agglomeration and urbanization economies in a rural context. Rural regions typically contain secondary cities and smaller towns with relatively more potential for sharing, matching and learning processes to take place (Duranton & Puga, 2004; Rodriguez-Pose, 2001). Rural households and firms may also have more to gain from increases in agglomeration because, when starting from a very small scale, the marginal effect from increases in the scale and diversity of economic activity may be larger in rural regions compared with urban ones (Artz, Kim, & Orazem, 2016). Hence, agglomeration effects are also valid in a rural setting, albeit on a different scale. McCormick (1999) discusses the importance of spatial interactions in the transmission of information in the context of developing countries. McCormick highlights the fact that face-to-face contacts and physical interactions should be particularly important ways in which to spread information and knowledge as these countries often have undeveloped infrastructures for communication and information exchange. Lewis, Barham, and Robinson (2011) present similar arguments and emphasize the fact that positive information externalities are particularly important in information-scarce environments, which is often the case in the rural areas of developing countries. Hence, the clustering of non-farm activities that encourage the diffusion of knowledge and information should assist rural households and farms to gain ideas, skills and information which increase their capacity to involve themselves in non-farm income-generating activities.

Several studies have focused on different dimensions of agglomeration economies and there is evidence that cross-industry spillovers play a relatively more important role in the context of developing countries compared with developed countries in which cluster specialization has been more central (Brülhart & Sbergami, 2009). This follows the idea that a diverse industrial structure enables interactions between a broad set of economic actors and the combination of knowledge from different types of industries which spurs the innovative and imitative potential

(Jacobs, 1969). From the perspective of rural households and farms, the more different economic activities that are found locally, the more opportunities should there be for observing and adapting new ideas and involving a diverse array of economic activities (Conley & Udry, 2001). Combes (2000) argues that the potential for information spillovers and co-dependency is also different across industries and that cross-industry spillovers are more prominently linked to services than to manufacturing. The underlying idea is that the service sector is much more heterogeneous in terms of its products, customers and supply/demand linkages compared with manufacturing. Service firms also interact with a diverse set of customers, suppliers and other economic actors, which enhances the possibility for network effects and knowledge spillovers. Goffette-Nagot and Schmitt (1999) discuss agglomeration economies and the spatial distribution of service activities in rural areas. They emphasize that services are more dispersed in geography and remain closer to households compared with manufacturing for reasons related to transportation costs. Hence, the type of scale economies present in rural areas should be more prominently linked to services compared with manufacturing. Bishop (2009) discusses two aspects related to the extent of service spillovers. The first is that the production and consumption processes in services often take place at the same time, which opens the possibility for knowledge diffusion between firms and their customers. The second is that services tend to be intangible, which makes them difficult to protect from imitators. Davis et al. (2014) address spillover effects and non-farm incomes in the context of the sub-Sahara and emphasize that local concentrations of services can be regarded as pull factors because they enhance a rural household's capacity to diversify its incomes and take part in non-farm activities. Hansson, Ferguson, Olofsson, and Rantamäki-Lahtinen (2013) and Barnes, Hansson, Manevska-Tasevska, Shrestha, and Thomson (2015) argue along these lines and emphasize that farmers located in areas with a more diversified industrial structure should have a greater potential to develop economies of scope in production, which makes them more flexible and adaptable compared with farmers in less diversified areas.

The focus of the present study is Rwanda, which presents some interesting features such as the growing importance of the service sector to the economy. Uwitonze and Heshmati (2016) note that the service sector has become the biggest contributor to gross domestic product (GDP), indicating a shift from an agricultural-based to a service-led economy, most notably driven by wholesale, retail trade, accommodation and food activities. Hence, the clustering of services that encourage the diffusion of knowledge and information should assist rural households and farms to gain ideas, skills and information which increases their capacity to take part in non-farm income-generating activities.

Empirical evidence

Rijkers et al. (2010) provide evidence from Ethiopia showing that manufacturing enterprises in urban areas are more productive than those in rural areas, supporting the view that the overall size and density of a local economy is important. Ali and Peerlings (2011) focus on Ethiopia and find that handloom firms in clusters with other microenterprises are more profitable and less likely to fail compared with those outside clusters. Owoo and Naudé (2017) report comparable results: that there are positive productivity effects associated with the co-location of non-farm enterprises in Ethiopia and Nigeria. Hence, there is evidence of agglomeration and urbanization economies in the context of the sub-Sahara. However, most of the studies have focused on spillovers that arise in urban areas and among clusters of microenterprises in urban areas. There is much less information on the extent that such locational factors may influence non-farm incomes among rural households and farms. Few studies have tested the possibility of spillovers from local non-farm activities on non-farm incomes in the context of the sub-Sahara and from the perspective of households. One exception is Ali and Peerlings (2011), who use data from Ethiopia and show that the local concentration of non-farm microenterprises in the same district increases the likelihood of a rural household to start a non-farm enterprise.

DATA AND EMPIRICAL MODEL

The empirical analysis is based on household-level survey data from two rounds of the Comprehensive Food Security and Vulnerability Analysis (CFSVA) survey conducted in 2006 and 2009. This is a nationwide survey of a random sample of 2717 households surveyed in 2006 and 5353 in 2009. In addition to information on demographics such as education, age and gender, the data include information on households' ownership of assets, agricultural activities, credit, remittances and non-farm incomes. The key feature of these data for present purposes is that they contain information about multiple income sources as households report their four main livelihood activities and the income generated from each. Hence, these data should include earnings from seasonal and part-time activity, which offer a more complete picture of the scale of non-farm earnings. As noted by Lanjouw and Lanjouw (2001) and Haggblade, Hazell, and Reardon (2010), surveys on household activities typically include only income from primary employment, with the implication that they often understate the importance of rural non-farm activity. A disadvantage of using the CFSVA data is that the surveys do not return to the same households and a panel cannot be formed. Even though there may be repeatedly sampled households, it is not possible to identify these. This gives rise to the problem of unobserved heterogeneity, which is more challenging to mitigate in repeated cross-sectional data.

In the absence of panel data, this study follows the approach of Shor, Bafumi, Keele, and Park (2007) and uses a multilevel model to mitigate unobserved heterogeneity and model spatial and temporal effects. Using this approach, households are nested in two geographical units: the local level and the more aggregated regional level, and unobserved heterogeneity is controlled for by including random intercepts at the different levels (the third section below outlines the estimated model in detail). The local level is an administrative unit that divides Rwanda into 420 units, whereas the regional level divides the country into 30 units. These units differ in their size and geographical scope as the local areas have an average total population size of 913 and the regions an average of 272,000.[3] For the geographical scope of the administrative units, see Figures A1 and A2 in Appendix A in the supplemental data online.

Dependent variable

Household per capita non-farm income is the dependent variable, defined as all income earned outside farming including income from commercial and entrepreneurial activity, e.g., handicraft, shops, business service, transport and non-farm wage work, divided by the number of household members. Similar definitions of non-farm income are applied by Owoo and Naudé (2017). The rationale for using per capita non-farm income instead of the share of non-farm income is to reduce the dependent variable from relations with the level and efficiency of agricultural activities.

Following the definition of rural areas developed by the National Institute of Statistics of Rwanda (NISR) (2016), which is based on distance from towns and population density, 95% of households in the sample are in rural areas. Considering the focus of the present paper, the 398 households located in urban areas (districts included in the province of Kigali City) are removed from the sample, meaning that the analysis and the results apply only to rural households. Using these household survey data implies that the sample includes rural households and farms that ground their income on both agricultural and non-agricultural activities. This highlights the necessity to consider jointly household and farm dimensions in the analysis. Descriptive statistics for the dependent variable are reported in Appendix B and Table B1 in the supplemental data online; descriptive statistics of the income sources reported in the data are presented in Table 1. Descriptive statistics are calculated using households in rural areas and do not include those 398 households located in urban areas. Incomes from non-agricultural daily labour account for the largest share (around 16%) followed by small commercial activity and private sector employment. Rural households also report that around 2% of their non-farm income comes from credit and remittances and 2% from other sources (aid and pensions). Household income from credit and remittances is not included in the calculation of the dependent variable but is controlled for in the regression via separate variables (see below). One issue is that the sources of the remittances are not reported in the data, i.e., if income from remittances is earned income or income transferred from non-household members. However, remittances account for a relatively small share of total income (around 1%) and robustness tests where remittances are included/excluded in the calculation of non-farm income are conducted to see if this influences the results. Table 1 shows that the bulk of household incomes, around 70%, comes from agricultural activities including incomes from agricultural production, fishing hunting and livestock. Even though agricultural income accounts for the largest share, around 50% of the households report at least one non-farm income-generating activity besides agriculture, indicating that such income is important. For a descriptive analysis of spatial dependencies using the Getis and Ord (1992) cluster analysis tool, see Appendix C in the supplemental data online. Figures C1 and C2 in Appendix C indicate significant clusters in both farm and non-farm economic activities, whereas the latter are clustered in areas that are located near the borders of the Democratic Republic of the Congo (DRC) and Burundi and near some of the largest cities.

Table 1. Decomposition of non-farm income among rural households.

Decomposition of the dependent variable, non-farm income	Mean (SD), 2006	Mean (SD), 2009
Commercial activity, entrepreneur	0.04	0.05
(e.g., transport, artisan)	(0.19)	(0.13)
Daily labour	0.11	0.13
	(0.23)	(0.25)
Private sector employee, civil	0.03	0.02
servant	(0.16)	(0.13)
Total	0.26	0.21
Observations	2546	5121

Note: SD, standard deviation.
Source: National Institute of Statistics of Rwanda (NISR). Besides the sources of non-farm income indicated above, households report that 2% comes from credit and remittances and 2% from transfers (aid and pensions). These sources are not included in the calculation of the dependent variable but controlled for in the estimations.

Independent variables

The independent variables in focus reflect clustering of local economic activity and the size of and distance to the nearest market. This study follows the approach of Frenken, Van Oort, and Verburg (2007) and Wixe (2015) and uses an entropy measure of industrial diversity (D_r), calculated with respect to the share of employees in each district who work within different industries. Industries are defined using the four- and two-digit International Standard Industrial Classification (ISIC) codes used to classify economic activities in Rwanda. The variable is calculated using the following:

$$D_r = -\sum_{g=1}^{G} E_g \ln E_g \tag{1}$$

where E_g denotes the share of total employment in each district that belongs to the same two-digit level where $g = 1, \ldots, G$. The measure captures variety in industry composition for the district and ranges from 0 to $\ln G$, where zero industrial diversity is reached when all employees are working in the same two-digit industry. The measure is calculated using the district level as a reference, which is the main administrative and political unit in

Rwanda (Figures A1 and A2 in Appendix A in the supplemental data online illustrate the administrative borders). The second variable is a location quotient (LQ) used to indicate the concentration of services in a location (Ali & Peerlings, 2011). This is calculated to measure how concentrated the service industry is in each location compared with the national average, as follows:

$$\mathrm{LQ}_I = \frac{e_I/e}{E_I/E} \tag{2}$$

where LQ_I denotes the location quotient of industry I (service) in the local area; e_I and e denote employment of industry I and total employment in the local area respectively; and E_I denotes employment of industry I at the national level and E total employment in the nation. If LQ > 1, the local area has a larger share of workers within the industry compared with the national average, indicating specialization in the industry. In the calculation of LQ, the employed are those whose primary activity is in the service sector and data do not allow one to consider those who are partly employed in the sector. Data limitations also prevent a breakdown of the service industry, and the analysis cannot examine differences across different types of services.

Table B1 in Appendix B in the supplemental data online provides definitions and summary statistics of the independent variables. The data used to calculate the measure of industrial diversity and the LQ come from The General Census of Population and Housing survey conducted in 2002 and the Establishment Census conducted by the NISR, implying that they reflect initial values. Although there are other more recent enterprise surveys, these are based on very small samples (around 60 firms) or realized after 2009. Given the fact that local and regional variables are often semi-fixed and change slowly over time, the data from 2002 should still capture the local and regional characteristics of focus and, more importantly, their relative importance. The advantage of combining data from these two surveys is that they are largely independent, which can mitigate concerns about correlated measurement errors when aggregating survey data from relatively small samples. The rationale for calculating the LQ at the local level is the argument that spatial spillovers related to clustering are very much place based and may be critical predictors within rather than between regions, as shown by Andersson, Klaesson, and Larsson (2016).

In line with Dorosh and Thurlow (2014), dense areas are *ceteris paribus* more likely to attract non-farm workers and enterprises. A density measure calculated with regards to the number of inhabitants per square kilometre in the district is included to control for this. Moreover, a variable that indicates the distance (Euclidean) from the centroid of the local area to the nearest town is included to control for market access and is hypothesized to lower transportation and transaction costs and provide access to market potential and non-farm jobs (Reardon et al., 2000).

Household-level controls

Several household-level variables are included, including measures of human capital (education and age), non-agricultural assets (ownership of means for communication and transportation, electricity and information and communication technology – ICT) and access to capital through credit and remittances. The selection of individual household variables and their definitions broadly follows the approach of the prior literature and are hypothesized to improve households' capacity to earn non-farm income as they lower transaction costs and information barriers and provide access to financial capital (e.g., Abdulai & CroleRees, 2001; Dabalen et al., 2004; Isaksson, 2013; Smith, Gordon, Meadows, & Zwick, 2001). Although remittances are hypothesized to spur a household's involvement in non-farm activities, as they represent a source of additional income, there is also the possibility that remittances can crowd out the change from farm activities being a substitute of non-farm income (Jensen, 2004). The purpose of including a broad set of household-level variables is to control for the level of income or wealth as there is no single variable that can control for that.

Other important indicators of household wealth in sub-Saharan countries, as in Rwanda, are households' ownership of land and livestock. These are important as households can use them as collateral for loans to start non-farm enterprises (Reardon, Delgado, & Matlon, 1992). They can also obtain revenue from animals and their by-products, which increases their non-farm income. Following Barrett et al. (2001), households' livestock holdings are calculated using cow-equivalents instead of the total number of livestock owned by the household to better reflect value and use.

Estimated model

Analyzing the determinants of households' non-farm earnings is challenging as there are likely correlations between individual outcomes and geographical variables as households' capability to earn such income is influenced by factors that are common in the local area or region. Manski (1993) denotes these types of correlations as endogenous social effects or neighbourhood effects, and they indicate the various channels through which society affects the individual. Specifically, they refer to the situation when the likelihood of an individual to behave in a certain way depends on the frequency of that behaviour in some reference group contacting the individual. Hence, economic activity in a given area cannot be assumed to be independent of the characteristics of the households that live there, nor can it be assumed to be independent of other geographically associated variables, such as the quality of the land (Lanjouw, Quizon, & Sparrow, 2001).

The empirical approach to account for spatial dependencies is to apply a multilevel model. This conceptualizes geographical space as a matter of group membership whereby households (denoted i) are nested in shared geographical units at the regional level (denoted j) and the local level (denoted k). A way to mitigate correlations between individual outcomes and geographical variables is to include instruments in the form of centred cluster means of the endogenous covariates (Snijders & Berkhof, 2006). The rationale is that a purely within variable, i.e., a variable that varies only within clusters, is necessarily uncorrelated with any between variable, constant within the clusters (Mundlak, 1978). The centred clustered mean of a level-1 covariate is thus a potential instrumental variable that is both internal and uncorrelated with the error term. Following the multilevel literature, the following three-level model is estimated:

$$y_{ijk} = \beta_0 + \boldsymbol{\beta}_1\boldsymbol{I}_{ijk} + \boldsymbol{\beta}_2\boldsymbol{R}_j + \boldsymbol{\beta}_3\boldsymbol{L}_k + \boldsymbol{\beta}_4\bar{\boldsymbol{I}}_k + u_j + u_{jk} + \epsilon_{ijk} \tag{3}$$

where y_{ijk} denotes the dependent variable; the per capita non-farm income of household i in region j and local area k. The fixed part of the model contains a vector of internal household characteristics $\boldsymbol{I}_{ijk}$, a vector of external characteristics measured at the regional level $\boldsymbol{R}_j$ and a vector of external characteristics measured at the local level $\boldsymbol{L}_k$. Moreover, $\bar{\boldsymbol{I}}_k$ is a vector of household characteristics included as centred group means at the local level to mitigate correlations between individual outcomes and geographical variables. These are selected using a Wald test of the null hypothesis that the coefficient of the cluster mean is zero at the 5% level. The model also contains a random part that accounts for the hierarchical structure of the data in that each j and k have random intercepts (u_j and u_{jk}), which are assumed to be independent (given the covariates) and normally distributed with zero mean and constant variance (Goldstein, 2011). The model in equation (2) can also be expanded to control for the fact that households are surveyed at different time points, which could influence the results. Skrondal and Rabe-Hesketh (2004) show that simultaneous and separate analysis of cross-sectional and longitudinal effects can be performed by including a fixed and random component in the following:

$$\begin{aligned} y_{ijk} = \beta_0 + \boldsymbol{\beta}_1\boldsymbol{I}_{ijk} + \boldsymbol{\beta}_2\boldsymbol{R}_j + \boldsymbol{\beta}_3\boldsymbol{L}_k + \boldsymbol{\beta}_4\bar{\boldsymbol{I}}_k + \beta_5\mathrm{T} + u_j \\ + u_{jk} + u_{jk}\mathrm{T} + \epsilon_{ijk} \end{aligned} \tag{4}$$

The model is identical to that above except for the inclusion of T, which denotes the year in which households are surveyed, and a fourth random component, u_{jk}T, which is a function of time. Using this approach, households are clustered in geography and in the time points at which they are surveyed, and unobserved spatial heterogeneity is modelled by including random intercepts and allowing for serial correlation among the higher-level k in the hierarchy (Snijders & Berkhof, 2006).

ESTIMATION RESULTS

Results from estimating the models are displayed in Table 2 with the per capita non-farm income as the dependent variable. The results for the full sample using equation (3) and combining the two years are shown in the two first specifications, but the model is also estimated for each year using equation (4) (specifications 3 and 4); the results are very similar. The first specification includes the household variables, the random components and the level-2 and -3 variables. The second specification substitutes between the diversity measure and the LQ, which are correlated. A correlation matrix is presented in Table D1 in Appendix D in the supplemental data online.

Starting with the geographical predictors, which are the focus of the present study, the coefficient of industrial diversity is positive and significant indicating that a higher initial diversity of economic activities is positively associated with per capita non-farm income. This is supportive of the idea that rural households and farms located in areas with a more diversified industrial structure are in a better position to earn non-farm income in comparison with their rural counterparts located in less diverse areas. This follows the idea that diverse economic environments provide more opportunities for observing and adapting ideas from others, which should enhance the possibility to take part in non-farm income-generating activities (Conley & Udry, 2001). The variable indicating clustering in services is also positive and significant across the estimations, suggesting that there are important spillover effects associated with such activities. This is in line with the argument that local concentrations of services can be seen as a pull factor that enhances a rural household's capacity to diversify its incomes and develop economies of scope in production (Barnes et al., 2015; Davis et al., 2014).[4] Results also show a negative and significant coefficient for distance to the nearest town, indicating that non-farm incomes fall as distance to the market increases. Overall, these results point to the importance of market linkages and knowledge spillover effects for households' participation in non-farm activities (Ellis, 2000).

Turning to household-level predictors, education and productive assets are positively associated with non-farm earnings. Results show that education is important when secondary schooling has been reached and that households with more assets (access to electricity and means for communication and transportation) have higher non-farm incomes. These results are broadly consistent with previous findings on the importance of pull factors, such as education, especially above primary schooling (e.g., Barrett et al., 2001). The finding that households' ownership of means for communication and transportation (ICT) is important is also in line with the idea that improved connectivity (e.g., using the internet as a communication channel) is a key factor in rural development (Malecki, 2003). Households' ownership of land and livestock is positive and significant, indicating that households with high non-farm incomes own larger stocks of land and cattle. This lend support to the idea that land increases households' investment in non-farm activities by providing, directly or indirectly, the capital needed to invest (Abdulai & CroleRees, 2001; Ellis, 2000). There is also a positive association between households' access to credit and remittances and non-farm earnings, which is consistent with the finding that credit and additional income via social ties (migrated family members) are key determinants of

Table 2. Regression results for the three-level multilevel model.

Fixed effects	(1) Combined sample Coefficient (SE)	(2) Combined sample Coefficient (SE)	(3) 2006 Coefficient (SE)	(4) 2009 Coefficient (SE)
Household-level predictors				
Household size	−0.511***	−0.501**	−0.222**	−0.423***
	(0.102)	(0.140)	(0.112)	(0.201)
Age (head)	−1.556***	−1.642***	−2.001***	−1.108***
	(0.105)	(0.107)	(0.234)	(0.225)
Education, primary	0.123**	0.221**	0.100	0.131
	(0.153)	(0.134)	(0.100)	(0.180)
Education, secondary	2.851***	2.733***	2.010***	2.182***
	(0.410)	(0.409)	(0.643)	(0.501)
Education, advanced	2.331***	2.301***	2.111**	2.193***
	(0.511)	(0.512)	(0.790)	(0.611)
Female	−0.371**	−0.370**	−0.221**	−0.345***
	(0.11)	(0.11)	(0.111)	(0.201)
Credit	0.251**	0.250**	0.119**	0.124***
	(0.101)	(0.113)	(0.099)	(0.014)
Remittances	1.531***	1.551***	0.861**	1.823***
	(0.252)	(0.234)	(0.390)	(0.317)
Per capita landholdings	0.034**	0.033**	0.009**	0.003*
	(0.004)	(0.002)	(0.000)	(0.000)
Livestock	0.020***	0.029***	0.010***	0.003
	(0.000)	(0.000)	(0.000)	(0.007)
Electricity	0.661***	0.662***	1.601***	0.777*
	(0.306)	(0.309)	(0.503)	(0.406)
Transportation	0.997	0.997	0.089	1.121**
	(0.646)	(0.646)	(0.990)	(0.830)
ICT	0.554***	0.554***	0.456***	0.501***
	(0.100)	(0.100)	(0.010)	(0.025)
Year	0.101***	0.101***	–	–
	(0.099)	(0.099)		
Geographical predictors				
Population density	0.101	0.101	0.171	0.129
	(0.129)	(0.129)	(0.101)	(0.171)
Distance to town	−0.466**	−0.463**	−0.494**	−0.395**
	(0.187)	(0.186)	(0.155)	(0.200)
Industrial diversity	0.101***	–	–	0.121***
	(0.012)			(0.011)
$LQ_{service}$	–	0.211***	0.187***	–
		(0.040)	(0.028)	
Constant	9.098***	9.110***	9.800***	0.321***
	(1.583)	(1.582)	(2.020)	(0.063)
Random effects				
Region (u_j)	0.831***	0.831***	0.545***	0.035***
	(0.242)	(0.242)	(0.214)	(0.004)
Local (u_{jk})	1.346***	1.200***	1.596***	0.059***
	(0.191)	(0.174)	(0.311)	(0.009)

(*Continued*)

Table 2. Continued.

Fixed effects	(1) Combined sample Coefficient (SE)	(2) Combined sample Coefficient (SE)	(3) 2006 Coefficient (SE)	(4) 2009 Coefficient (SE)
Year (u_{jk}T)	2.75e–10***	3.48e–11***	–	–
	(1.42e–11)	(1.01e–11)		
ICC: region	0.037***	0.038***	0.034***	0.030***
ICC: local | regional	0.102***	0.101***	0.117***	0.112***
Wald test	818.91***	820.84***	333.91***	677.55***
Observations	7677	7466	2546	5121

Notes: Sample weights are included in the estimations. For brevity, the coefficients for the clustered level-1 covariates are not reported but are included in all estimations to mitigate endogeneity across levels.
Dependent variable: per capita non-farm income of rural households and farms.
ICC, intraclass correlation coefficient; ICT, information and communication technology; LQ, location quotient; SE, standard error.
***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

household income diversification and risk-minimizing strategies (Bigsten, 1996; Ellis, 2000). Although the results are consistent with theory and previous findings, it is challenging to capture the level of poverty, which could influence the results. There is no single variable that can control for household wealth, and in the absence of panel data this study uses a broad set of household-level control variables and a multilevel model intended to mitigate unobserved heterogeneity.

Turning to the random effects, which quantify the average deviation from the mean (β_0) at each level and capture unobserved heterogeneity (Table 2), these show that there are significant spatial dependencies which are controlled for via the random effects. This can be described using the ratio of the between-cluster variance to the total variance, i.e., the intraclass correlation coefficient (ICC), also reported in Table 2. The ICC gives the proportion of the total variance in non-farm income accounted for by the local and regional levels and can be interpreted as the correlation among observations within the same geographical unit. Intuitively, the random effects reflect that the more disaggregated local level explains most of the variance in the dependent variable compared with the regional level.

CONCLUSIONS

This paper tests the role of agglomeration effects on non-farm earnings among rural households and farms in Rwanda. While most previous studies on clustering, in the context of rural Africa, focus on firms and industries (Owoo & Naudé, 2017), this paper argues that there are reasons to consider the extent to which spatial spillovers may influence non-farm earnings among rural households. Specifically, it argues that the decision to begin non-farm activities and the income earned should be linked to knowledge and information spillovers and opportunities linked to the diversity of other economic activities present in the rural economy, and particularly to local concentrations in services. This is based on the idea that the diffusion of non-farm activities in rural areas stems from knowledge spillovers linked to sharing of information, example and imitation, in the local communities (Jalan & Ravallion, 2002).

To test the relevance of the arguments, this paper uses household-level data from Rwanda obtained from two rounds of the CFSVA survey. A three-level multilevel model is used to mitigate correlations between individual outcomes and geographical variables. Results show that a higher initial concentration of service activities is positively associated with non-farm income among rural households and farms for both years studied. Results point to the importance of market access and knowledge spillover effects present in rural areas for households' participation in non-farm activities. These results are consistent with the findings in previous studies that focus on the role played by clustering in explaining the productivity and survival chances of non-farm firms in sub-Saharan Africa (Ali & Peerlings, 2011; Rijkers et al., 2010). However, the paper adds to the existing literature by differentiating local non-farm activities and testing the possibility of externalities linked to services (Combes, 2000). Increasing the understanding on spillovers linked to service is important when considering the wider process of structural change, which is about to transform Rwanda from an agricultural-based economy to a service-oriented one (Uwitonze & Heshmati, 2016). The findings also bear on policy. Recent policies in Rwanda have involved a considerable emphasis on developing the service sector on the assumption that such activities may generate important external effects for a broader set of economic agents. The results of this paper lend support for the presence of such external effects, but they also illustrate the need to consider local factors in the formation of policy.

Although the results of this study are consistent with the idea that knowledge spillovers arise from the clustering of local economic activities, the analysis cannot unravel the mechanisms behind this fact. The hypothesis that personal/community linkages affect households' decisions has no empirical evidence in the present paper, but it would be relevant to disentangle these effects in further studies. In this respect, this study opens the way for studies that attempt to disentangle the effects, perhaps through a qualitative approach and interviews. Moreover, sectoral heterogeneity in services could be further analyzed as there likely within-industry differences (Bishop, 2009). This could increase the understanding of how different measures of local diversity affect non-farm growth.

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DISCLOSURE STATEMENT

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NOTES

1. The term 'non-farm' is used here to refer to all income earned outside farming including that from commercial and entrepreneurial activity, e.g., handicraft, shops, business service, transport and non-farm wage work (Haggblade et al., 2010; Owoo & Naudé, 2017).
2. Even though physical interactions are often seen as a positive character that helps to communicate and innovate, there is also the possibility of negative effects. A closed social network may, for instance, result in a loss of flexibility and lock-in as actors may choose to rely on existing linkages rather than on establishing linkages to otherwise unrelated actors (Nooteboom, 2004). Most studies on related issues find positive spatial and social interaction effects and bridging external networks are likely important for small firms and farm households as they often lack the necessary internal knowledge and information to cope with changes in the external environment, risk and negative shocks (Wollni & Andersson, 2014). Lanjouw et al. (2001), for instance, show that social interactions, measured as time devoted to communal activities, are important in stimulating Tanzanian households to engage in non-farm activity.
3. The National Institute of Statistics of Rwanda (NISR) denotes these administrative units' sectors (here local) and districts (here regional). To avoid confusing the sector level with industry (e.g., non-farm sector), this study consequently uses 'local' and 'regional' to denote these geographical units.
4. A locational quotient, calculated to reflect local specialization in manufacturing in relation to the nation as a whole, was also tested, but the coefficient remains insignificant across the estimation.

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