CROP DIVERSIFICATION, SPECIALIZATION AND PRODUCTIVITY IN RWANDAN AGRICULTURE

Marvin E. Mbassana and Pia Nilsson***

** College of Business and Economics (CBE), University of Rwanda. * Jönköping International Business School, Sweden

ABSTRACT

The purpose of this paper is to analyse agricultural growth in Rwanda focusing on the role of crop specialization and diversification. Agricultural growth is associated with growth in the stock of conventional input factors in terms of land, labour and to intra-district allocation of land use in terms of crop shares. A production function is estimated based on panel data at the district level over the years 2006-2013 covering the main crops. Results show that conventional inputs in the form of land and labour intensity are the main source of agricultural growth. The significance of both the Herfindahl-Hirshman and the Shannon entropy index, thought to reflect crop specialization and crop diversification are supported by the data. Estimating the model across the main crops to indicate complementary effects show that it is profoundly the cultivation of beans and cassava that give rise to such complementarities.

Keywords: agricultural productivity; crop diversification; specialization; economic growth

INTRODUCTION

Rwanda belong to one of the most densely populated countries in the world and its agricultural sector is faced with problems in terms of land scarcity, land degradation and altered climate conditions. Considering that agriculture is the main source of employment and a key determinant of national food supply, developing a sector that exhibits economies of scale enough to increase both food security and export intensity is a major concern. Alike many other sub-Saharan countries, the Rwandan agricultural sector is dominated by small scale diversified farming systems highly reliant on rain fed and the supply of cultivatable land, which makes the country particularly sensitive to climate change. In view of the low level of economic diversification and that future warming seems unavoidable (Rosensweig and Hillel 1998; IPCC 2007a), economic growth in Rwanda can be strongly associated with agricultural growth and the outcome of climate change adaptation strategies.

Given the capacity constrains in Rwandan agriculture and the limited possibilities to increase the supply of cultivable land, agricultural policy has primarily been focused on introducing economic incentives that encourage the production of a few selected crops as a means to increase specialization and intensify production. In brief, economic incentives in the form of input subsidies have been introduced to encourage the substitution of less profitable crops to high-value crops, building on a land consolidation model in which farmers, in a given district, grow the priority food crops in a synchronized fashion while keeping their land rights intact.[1] A number of studies lend support to the view that specialization increase agricultural production and such strategies have long been argued to bring efficiency gains from the division of labour and the organization of resources (Smith 1776; Huffman and Evenson 2000; Kurosaki 2003). However, there are also studies that argue on the contrary and show empirically that crop diversification is a more desired strategy to obtain agricultural growth as it reduces the risk associated with climate change variability and contribute to (bio)diversity (Matson et al. 1997; Lin 2011). Although such risk averse land use management systems are often thought to suffer from low productivity, studies have shown that the complementarities that arise from diversified farming systems are able to bring productivity gains and protect farmers' incomes from climate change variability and extreme events (Coelli and Fleming 2004; DiFalco and Veronesi 2013). Given that crop diversification can be seen as a strategy to both obtain economic gains and build resilience into agriculture it is becoming increasingly important to study the productivity gains associated with such farming.

The purpose of this paper is to contribute to the literature by studying the effects of crop specialization and diversification focusing on agricultural productivity growth in Rwanda. Growth in the value of total agricultural output is associated with changes in crop composition at the district level over the years 2006-2013 and the estimated production function is specified to account for increases in crop specialization and diversification by means of a concentration index (Herfindahl-Hirshman) and a Shannon entropy measure. The presence of complementarities among the crops are addressed by estimating the model for five of the main crops independently. The findings in this study lend support to the presence of both specialization and diversification efficiencies, although the productivity gains obtained from crop diversification are indicated to have little economic significance. Both scale- and complementary effects are found among the crops, which mainly arise in the cultivation of beans and cassava.

It should be noted that although we are able to make an important contribution by studying the influence of crop diversification in view of Rwandan agricultural growth, which has not been done before, we are unable to address causal effects or the influence of policy in explaining such growth. The lack of consistent and disaggregated cross-sectional time series data prevents a counterfactual analysis with regards to the effect of input subsidies on productivity growth. Yet, the empirical approach is designed to correct for endogeneity bias with regards to the change in crop composition and unobserved district-specific factors by utilizing an instrumental variable approach that deals with endogeneity in the context of panel data (Mundlak 1978; Chamberlain 1982).

The paper is organized in the following way: Section 2 presents the theoretical background and connects this paper to the relevant literature in the field. Section 3 describes the data used in the empirical analysis followed by a description of the estimation

[1] With reference to The Organic Law Organic Law N 08/2005 of 14/07/2005 and the Crop Intensification Program (CIP 2007).

procedure. The regression results are presented in Section 4 and Section 5 concludes the paper.

LITERATURE REVIEW

2.1. Agriculture

Agriculture is the predominant sector in the Rwandan economy and employs about 80 percent of the workforce and contributes to 35 percent of gross domestic product, comparable figures apply to most sub-Saharan countries (Sagihr 2014). That agriculture is the major land use and source of labour activity implies that it provides significant economic, social and cultural activities and a wide range of services to local communities (Howden et al. 2007). Kim, Larsen and Theus (2009) observe that sustainable development is highly influenced by the performance of the agricultural sector and that 45 percent of the developing world's population lives in household that are dependent on agriculture. Therefore, economic growth and improvements in environmental and social welfare in these countries can be intrinsically linked to growth in their agricultural sectors (Saghir 2014).

The main constraint to agricultural growth in Rwanda, as in most agricultural societies, can be linked to sluggish technological progress, diminishing marginal returns to agriculture and altered climate conditions (Nordhaus et al. 1996; Kim and Heshmati 2014). The largest negative impact of climate change is often shown to adhere to the agricultural sector and particularly to agriculture in developing countries (Mendelsohn 2009; Lobell et al. 2011). Studies that focus on sub-Saharan countries lend support to this argument and argue that agriculture will be strongly and negatively affected by global warming since the already vulnerable and low productive land will be exposed to further pressure in terms of higher temperatures and lower precipitation (Berry et al. 2006: DiFalco and Veronesi 2013). Although adaptation strategies are likely to reduce some of the worse predicted outcomes, climate change is expected to cause large damage to agricultural sectors and individual farmers across Africa (Parry et al. 2004; Schlenker and Lobell 2010). For Rwanda, being a landlocked country with limited supply of arable land, high population density and high dependence on rain fed agriculture, finding strategies to mitigate such damage is a major concern.[2]

There is a growing research that focuses on the relations between agricultural productivity, climate change and adaptation strategies. A central question in this literature is whether it is possible for countries, regions and individual farmers to achieve climate change adaptation and at the same time maintain or improve agricultural productivity (Acemoglu et al. 2009; Nordhaus and Boyer 2000). Although the adverse effects are dependent on country specifics (Tilman et al. 2002), there seems to be an agreement that the outcome of long-term changes in external conditions is highly dependent on the ability to adapt production techniques and build resilience into agricultural systems (Mendelsohn and Dinar 2003; Reidsma et al. 2010).

[2] The cost of climate change has been estimated to about one percent of gross domestic product and one third of Rwandan households report that they are being adversely affected by environmental problems, most often in terms of erosion, reduced soil fertility, and damaging rains. Stockholm Environment Institute (2009), Economics of climate change in Rwanda.

2.2 Specialization vs. diversification

Specialization has long been seen as an integral part in the structural transformation of the agricultural sector as a means to intensify production and achieve growth (Smith 1776; North 1959). From the perspective of agricultural productivity, specialization is expected to lead to efficiency gains in the division of labour and the management of resources (Coelli and Fleming 2004). Building on such arguments, crop intensification by the use of high-yielding crops along with fertilization, irrigation and pesticides has been the dominating source of agricultural growth during the past decades (Matson et al. 1997). Although the productivity gains are shown to vary across farming systems and countries several studies have found a positive relation between specialization and agricultural growth. In studies focusing on land and labour productivity across countries, including the U.S (Huffman and Evenson 2000), Pakistan (Kurosaki 2003) and China (Rae and Zhang 2009), it is found that increasing the degree of specialization leads to productivity gains and increased rural incomes. Although most of the previous results rely heavily on the conditions that apply in developing countries, they generally support the hypothesis that specialization brings increasing returns.

Although increased agricultural specialization is generally hypothesized to be beneficial from the point of view of agricultural output growth, the awareness that climate change bring negative effects have increased the desire to build resilience into agricultural systems (Walker 1995; Lin 2011). The concept of resilience stems from the insurance hypothesis that has both an ecological and an economic interpretation. From the point of view of ecology, diverse farming systems provide an insurance against climatic fluctuations since different crops respond differently to changes in external conditions, implying that diverse systems are more tolerant and predictable compared to specialized systems (Kaiser et al. 1993; Altieri 2002). Moreover, since diverse cropping systems provide a wider range of ecosystem services which many rural communities depend on, the potential gains derived from such systems go beyond those that can be priced and directly measured. Thus, drastic changes in crop composition or removing crops from the system may affect the entire capacity to generate future ecosystem services (Folke et al. 2004).

Although economic incentives to become more specialized are primarily driven by government policy (subsidies and pricing policy) and production technology (Kim et al. 2012), the economic incentives to become more diversified can be seen as a response to altered climate conditions and as a strategy to spread or avoid risk. From the perspective of the individual farmer, there exist strong incentives to select a portfolio of farming activities in order to stabilize income flows and consumption. This is particularly true for developing countries as the largest negative impact of climate change is expected to adhere to these countries (Mendelsohn and Dinar 2003). Resilient agricultural systems can thus provide a more stable and reliable source of income such that farmers become less vulnerable to drastic changes in climatic conditions (Loreau and Hector 2001).

Gulati and Tewari (2004) note that the concept of diversification carries different meaning to different people at different levels. In agriculture, diversification will mean a shift of resources from one crop to a larger mix of crops with the ultimate goal of improving income and life conditions. In a pioneering study Grimes (1929) argues that diversification of agricultural production results in increased income and improved agricultural conditions. Benefits from crop diversity may also come in the form of productivity gains derived from the complementary effects that arise across a diversified set of outputs (Baumol et al. 1982; Chavas and Kim 2010) even though these advantages in certain circumstances are conditioned by the number of farmers attempting to secure them (Grimes, 1929). In general, when farmers experience hardship they either turn to the production of new products or they increase the production of products that had very little importance in their farming experience (Grimes, 1929). Studies that address the benefits associated with diverse farming systems show that implementing crop diversity is a productive way to enhance resilience and protect farmers' incomes from climate variability and extreme events (Lin 2011; Di Falco and Veronesi 2013). This is particularly true for small scale farmers who are highly dependent on resilience for their livelihood since they have few alternative sources of income and employment and little capital to invest in expensive adaptation strategies (Lin 2011). Hence, crop diversification can be seen to work in the opposite to specialization.

A recent counterfactual analysis by Di Falco and Veronesi (2013), focusing on Ethiopian farmers, show that adaptation to climate change based on a portfolio of strategies significantly increase farm net revenues and play an important role in reducing food insecurity of farm households. Chavas and Kim (2010) show that benefits from diversification can be decomposed into; benefits derived from complementary effects among a differentiated set of outputs and benefits derived from scale effects among the outputs. Such a decomposition can be useful in order to understand the benefits associated with crop diversification as diversity can be implemented in a variety of scales allowing farmers to build resilience into their farming systems which, at the same time, allows for productivity growth (Adger et al. 2005; Kim et al. 2012). Crop diversification might thus provide a link between altered climate conditions and resilience as biodiversity is a requirement to ensure the functionality of ecosystems (Heal 2000; Adger 2006). Even though advantages of diversification to individual farmers could be numerous, it is worth noting that if a large number of farmers make similar changes the advantage can quickly disappear.

Though there exist several theoretical arguments to support the significance of both specialization and diversification strategies in increasing agricultural growth, the empirical evidence show mixed effects across countries and a key question raised in the current literature is whether agricultural productivity is driven by specialization or by diversity (Tilman et al. 2002; Coelli and Fleming 2004).

METHODOLOGY

3.1. Research design, Population and sampling procedures

In order to address the influence of crop specialization and diversification on agricultural productivity a production function is estimated based on data provided by the ministry of agriculture in Rwanda. Considering data availability, the district level was used as the unit of analysis which was a form of local administration unit that divide the country into 30 districts according to the current division. District boundaries have been changed several times during the last decade, which created problems when it came to the possibility to consistently compile data that stretched over longer time periods. Prior to 2006, agricultural statistics were reported at the more aggregated 4 provinces levels, during 2006-2010 the 28 districts division is used and after 2010 the 30 districts division that disaggregates Kigali into three districts was used (Gasabo, Kicukiro and Nyarugenge).

Although a longer time period would be preferable to address dynamic agricultural transformation with regards to specialization/diversification, data availability did not allow an analysis that stretches prior to 2006.

In this study, the 28 districts division was used as reference and the analysis cover the years 2006-2013. Since each year consist of two growing seasons (from September to January: season A and from February to June: season B), for which data was available, the studied time span result in a panel with 15 time periods and 420 observations. For each of the 28 districts and growing seasons, data for cropped area and production volume are compiled for 15 of the main crops; beans, bananas, maize, cassava, sorghum, Irish potatoes, sweet potatoes, soybeans, vegetables, peas, fruits, wheat, yam and taro, groundnuts and rice. Out of these crops, the priority (high-value) food crops are beans, maize, cassava, Irish potatoes, soybeans, wheat and rice. Descriptive statistics on the variables are summarized in Table 2 and variable definitions are presented in Table 3. Summary statistics show that beans, bananas, maize and cassava comprise the highest crop shares. At the average, 21 percent of harvested land was devoted to the production of beans, 19 percent to the production of bananas and 18 and 8 percent to the cultivation of maize and cassava respectively.

In order to obtain a measure of agricultural productivity, the value of aggregate production volumes were calculated using annual crop prices from FAO (in USD 2006) to obtain the value of total agricultural output for each district. Output was then normalized on a per hectare basis to avoid problems of heteroscedasticity (Frisvold and Ingram, 1995). Growth in agricultural productivity over the studied time period and by district is illustrated in Figure 1.

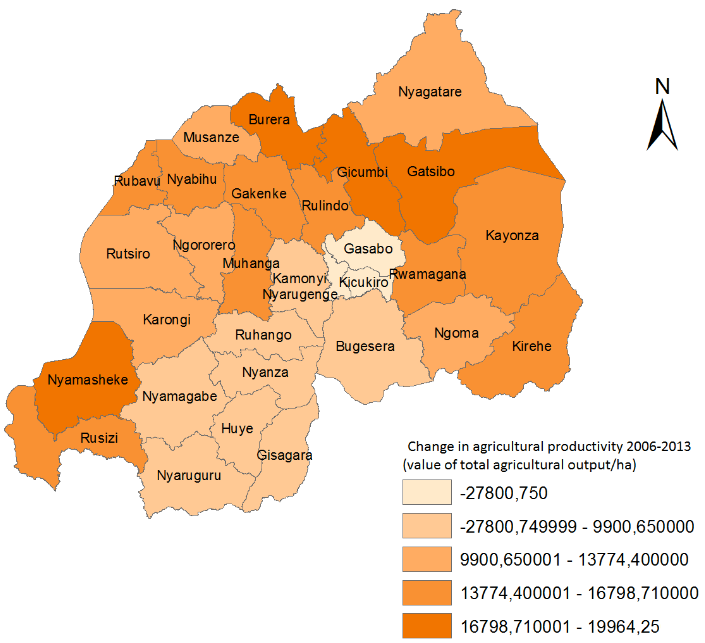

Figure 1. Growth in agricultural productivity (value of total agricultural output/ha in USD 2006) 2006-2013.

As can be seen from the figure, agricultural productivity in Rwanda has been increasing most profoundly in the districts located in the eastern, northern and western provinces, with the exception of Bugesera (eastern province) which has faced a decline in agricultural productivity alike most of the districts located in the southern province and Kigali city (Gasabo, Kicukiro and Nyaruhenge). Most of the regions located in the Southern Province have witnessed a low growth or decline in agricultural productivity over the period. These districts face problems with low soli quality, problematic climate conditions and belong to the poorest districts in the country. There are also districts that show high growth in productivity. Nyamasheke belongs to the districts that have experienced a higher growth in agricultural productivity compared to its neighboring regions. This district lies near the Ugandan border and has benefited from introducing new technical innovations to improve agricultural productivity mainly in the production, packing and distribution of rice. Overall, the growth patterns shown in Figure 1 establish that most of the districts in the Southern Province are lagging behind in terms of agricultural productivity.

3.2 Estimated model and variables

To address the influence of specialization and crop composition on agricultural productivity we estimate the following production function:

$$\ln y_{it} = \alpha_{it} + \sum_{z=1}^{r} \beta_z X_{zit} + \sum_{k=1}^{m} \beta_k Z_{kit} + \tau_t + \nu_i + \varepsilon_{it} \quad (1)$$

where y_{it} denote aggregate agricultural output per hectare for the *i*th district at time *t*. The *z* independent variables are measures of conventional input factors in terms of labor, land and soil quality (temperature and precipitation) and the *k* independent variables include inputs in the form of land devoted to the cultivation of the main crops, β_z and Z_k are the corresponding coefficient of each covariate. From the crop shares, measures of crop specialization and diversification are calculated and included in the estimated model as described below. Moreover, building on the decomposition suggested by Chavas and Kim (2010), the effects of diversification is studied in terms of scale effects among the inputs by introducing flexibility into the estimated equation and in terms of complementary effects by estimating separate production functions for the main crops.

As discussed, agricultural productivity differences are related to a range of factors. In addition to land and labor inputs, local externalities, the structure of the regional agricultural sector and land management are likely to be influential factors (Xu et al., 1993). Furthermore, farmers land use decisions and the spatial shift of crops over time are likely highly dependent on both managerial abilities and agricultural policies. This necessitates an empirical approach that controls for both unobserved district heterogeneity and corrects for endogeneity bias with regards to the shift of crops over time. To mitigate the problems associated with unobserved heterogeneity and potential endogeneity, prior studies have used time invariant fixed effects (Kirwan and Roberts 2010; Ciaian et al., 2012) or soil quality control variables (Livanis et al., 2016). In this study, district fixed effects ν_i are included to control for unobserved heterogeneity (Mundlak, 1978;

Wooldridge, 2002), and potential endogeneity problems are addressed by utilizing an instrumental variable approach based on the mean of the endogenous variables (Mundlak, 1978; Chamberlain, 1982; Hausman and Taylor, 1981). The remaining components τ_t and ε_{it} denote a time-variant time trend and an idiosyncratic error term.

3.3 Measuring crop specialization/diversification

The independent variables in focus are the *k* measures of crop specialization and diversification constructed to reflect the effects of the spatial shift of crops over time. The Hirschman-herfindahl index (Herfindahl, 1950 or Hirschman, 1964) has been widely used in the measurement of market concentration and is shown to perform best empirically compared to other related measures of specialization (Jacquemin and Berry, 1979). It has also been extensively applied in the study of agricultural specialization and diversification (Kurosaki, 2003; Rahman, 2009; Kim et al., 2012). Applying the index to measure crop specialization among the main 15 crops implies that it can be specified as:

$$HHI_{it} = \sum_{c=1}^{15} a_{cit}^{\alpha} \quad (2)$$

where a_{it} denote the share of harvested land (*A*) devoted to the cultivation of the $c = 1,...15$ crops in district *i* at time *t.* Although the value of α is often set equal to 2 it can be taken to be arbitrary. Since the chosen value implicitly places a weight on the dominant crops there is a risk of introducing a bias (Chisholm and Oeppen, 1973). As an alternative Keeble and Hauser (1971) suggest an approach that leads to more appropriate weights by using the square root of the HHI. Hence, for $\alpha = 2$ and $c = 1,...15$ the following measure of crop specialization is applied:

$$HHI_{KH_{it}} = \sqrt{\sum_{c=1}^{15} a_{cit}^{\alpha}} \quad (3)$$

where a value of 1 indicates complete crop specialization and approaches the lower bound with the increase in the extent of crop diversification. Descriptive statistics in Table 2 show that the average degree of specialization as measured by HHI_{KH} is 0.16, indicating a very low degree of specialization in the Rwandan agricultural sector. Following from the theoretical arguments outlined in section 2, crop concentration is hypothesized to have a positive effect on agricultural productivity indicating efficiency gains obtained from the division of labor and organization of resources (Coelli and Fleming, 2004). Although the effects of specialization is shown to be both country and industry-specific (Renski, 2011), the high level of diversification in the Rwandan agricultural sector makes it reasonable to believe that marginal increases in specialization contribute positively to agricultural productivity growth.[3]

Although it would be straightforward to obtain a measure of crop diversification by using the Herfindahl index as the lower bound indicate complete diversification, Jacquemin and Berry (1979) show that a measure of diversification that builds on the entropy approach is a more appropriate measure compared to the inverse HHI. The entropy

[3] The average farm size is 0.7 ha and the trend is towards even smaller plots (MINAGRI, 2012).

measure is argued to be more sensitive than the Herfindahl index with regards to very small proportions (Stigler 1968) and should thus be more meaningful as a measure of diversity at high levels of diversification. Hence, the Shannon (1948) index is used to measure the entropy of harvested area (A), defined in the following way:

$$H(A) = -\sum_{c=1}^{15} a_{cit} \ln(a_{cit}) \tag{4}$$

Based on the theoretical arguments outlined in section 2, the expectation is a positive relation between crop diversification as measured by Equation 4 and agricultural productivity. A positive impact is hypothesized to reflect benefits derived from income stability (Di Falco and Veronesi, 2013) and from scale and complementary effects (Chavas and Kim, 2007; Kim et al., 2012). The average degree of crop specialization and diversification as measured by equations 3 and 4 for the ten top districts are shown in Table 1.

Table 1. Ratios of Herfindahl and entropy indices, average values 2006-2013

		Index of crop specialization and diversification			
Rank	District	Herfindahl (HHI_{KH})	Rank	District	Entropy ($H(A)$)
1	Kirehe	0.45	1	Nyaruguru	2.08
2	Gakenke	0.44	2	Ngororero	2.03
3	Kayonza	0.43	3	Nyamagabe	2.03
4	Ngoma	0.43	4	Rutsiro	2.00
5	Rwamagana	0.42	5	Nyanza	1.97
6	Rubavo	0.42	6	Huye	1.95
7	Gatsibo	0.41	7	Gisagara	1.94
8	Nyageteree	0.40	8	Karongi	1.94
9	Bughesera	0.40	9	Gicumbi	1.93
10	Rulindo	0.40	10	kamonyi	1.92

3.4 Conventional inputs

Conventional inputs in the form of labor and land are included in the estimations. Given that cross-section time series data that consistently measure the number of workers active in the agricultural sector (or labour input in terms of worked hours) unavailable, labor intensity is indicted by the log of the ratio of population to harvested land. Since this is just a measure of rural population density there is a risk that the importance of labor in explaining productivity growth may be overestimated, which is discussed later. For other key variables, such as capital and average farm size, data is either unavailable or inconsistently measured and can therefore not be controlled for directly in the estimations. The log of the total number of hectares of harvested land is included as a size measure and unobserved heterogeneity at the district level (unobserved managerial abilities, water supply, irrigation, capital) is controlled for by the district fixed effects.

Differences in agricultural productivity are highly dependent on differences in natural prerequisites for agriculture in terms of climate conditions, soil quality and altitude. These factors are often measured empirically by the use of categorical variables and are often treated as exogenous variables that change slowly over time. Most of the studies that include such variables in their studies show that natural prerequisites have a significant impact on agricultural productivity (Kaptenaki and Rosenzweigh, 1997; Alston et al., 2010). In this study, soil quality and natural prerequisites are indicated by the use of climate variables defined in terms of the seasonal averages (by growing season A and B) of precipitation and temperature (Mendehlson, 2008). Moreover, a time trend is included among the variables, thought to reflect technological progress during the studied time period (Kim et al., 2003), defined as the average annual agricultural growth rate of the neighboring countries that have with a similar structure of their agricultural sectors (Congo, Ethiopia, Kenya, Tanzania and Uganda). The rational for including a time trend based on neighboring countries is the possible endogeneity between agricultural growth and agricultural policy during the period.

Table 2. Summary statistics

Variables	Min	Max	Mean	Std.Dev.
Agricultural output/ha	5891.587	51949.99	23385.13	6577.725
Total harvested area	0.122	1	0.407	0.167
Population density	121.516	1575.795	468.726	245.727
Rural population density	662.421	1035.783	133.147	148.733
Average precipitation	0.521	9.572	4.036	1.4055
Average temperature	14.47	29.840	24.671	3.041
Crop specialization (HHI_{KH})	0.005	1.108	0.396	0.076
Crop diversification (H(A))	0.065	3.465	2.083	0.251
t	2.828	5.070	3.824	0.785
Cropshare				

Beans	0.002	0.788	0.212	0.069
Bananas	0.002	0.729	0.195	0.072
Maize	0.0003	0.428	0.101	0.075
Cassava	0	0.900	0.101	0.070
Sorghum	0	0.35	0.081	0.082
Irish potatoes	0	0.437	0.079	0.073
Sweet potatoes	0	0.210	0.069	0.038
Soybeans	0	0.200	0.030	0.027
Vegetables	0	0.200	0.026	0.019
Peas	0	0.11	0.022	0.022
Fruits	0	0.094	0.021	0.119
Wheat	0	0.191	0.020	0.034
Yam & Toro	0	0.100	0.015	0.013
Groundnuts	0	0.070	0.012	0.015
Rice	0	0.090	0.009	0.013
Province				
North	0	1	0.178	0.383
South	0	1	0.285	0.452
West	0	1	0.250	0.433
East	0	1	0.250	0.433
Kigali	0	1	0.035	0.186

Table 3. Variable definitions

Variable	Definition
Agricultural output per/ha	Dependent variable. The natural logarithm of the total value of agricultural output in kg per hectare. Calculated using crop prices by district and growing season. Sources: prices are obtained from FAO and production data from the ministry of agriculture in Rwanda.
Harvested area	The natural logarithm of the total number of hectares of

	harvested area by district and growing season. Source: MINAGRI, Rwanda.
Rural population density	The natural logarithm of the total number of inhabitants per square kilometer harvested land by district and year. Source: Ministry of agriculture Rwanda.
Crop specialization HHI_{HT}	Measured by Eq.3.
Crop diversification $H(A)$	Measured by Eq. 4.
Average precipitation	Average precipitation by district and growing season. Source: Rwanda meteorology agency.
Average temperature	Average max temperature by district and growing season. Source: Rwanda meteorology agency.
Cropshare	Share of total harvested land devoted to key crops by district and growing season. Key crops include sorghum, maize, wheat, rice, beans, peas, groundnuts, soybeans, banana, Irish potatoes, sweet potatoes, yam & taro, cassava, vegetables and fruits. Source: Ministry of agriculture Rwanda
t	Time trend measured as the average annual agricultural growth rate in Congo, Ethiopia, Kenya, Tanzania and Uganda 2006-2013. Source: FAO

RESULTS AND DISCUSSIONS

4.1. Estimation results (dependent variable = the log of agricultural output per/ha)

Results from estimating the production function (Equation 1) are presented in Tables 4-6. Since the crop specialization and diversification measures are correlated with each other and with the crops shares (from which they are constructed) these are estimated in separately specifications. Table 4 display the results from the inclusion of conventional inputs and the crop specialization and diversification measures, Table 5 display the results from including the crop shares and their squared covariates and Table 6 display the results from estimations across the main crops. As discussed, the production function is estimated using the crop shares along with their squared covariates to address the presence of scale effects (Table 5) and then estimated across the main crops to address complementary effects (Table 6). The empirical approach is to use the district fixed effects approach (Mundlak, 1978) and then re-estimate the models using an instrumental variable approach (Hausman and Tylor, 1981) to mitigate the endogeneity bias hypothesized to be associated with the change in crop composition over time.[4] A similar approach was used in Kim et al. (2012) in their study of the productivity of Korean rice farmers. Following their approach, we treat most of the input factors as time-varying endogenous variables and treat controls for natural prerequisites as either time-varying exogenous variables (average temperature and precipitation) or time-invariant exogenous variables (regional fixed effects). As shown in Table 4 and 5, the results are similar across the estimations suggesting that the results are robust to the inclusion of the means.

Starting with the results in Table 4, the coefficient value of the Herfindahl index is positive and statistically significant (specification 1) indicating that the effect of specialization as measured by the concentration of crops shares is positively related with agricultural productivity. The coefficient value of the entropy measure (specification 2) is also positive and statistically significant although its economic significance appears to be relatively low evaluated based on the magnitude of the coefficient value. These results lend support to the theoretical arguments concerning the expected efficiency gains associated with increases in specialization; they also lend support to the existence of diversification efficiencies (Coelli and Fleming 2004; Rahman, 2009), although these are indicated to be small. Results are intuitive as they reflect increased concentration of crop acreage in districts with growing productivity, indeed a rapid specialization in crop production has been observed in Rwanda since the introduction of input subsidies in 2008. However we are unable to draw any conclusions concerning the direction of these relationships or address the significance of policy with regards to the increase in crop concentration.

Conventional input factors have their anticipated signs in both specifications. The coefficient values of both land and labor are positive and statistically significant, indicating that districts that are more endowed with harvestable land and labor are associated with higher agricultural productivity growth. The supply of harvested land is indicated to be a relatively more important input factor compared to labor, which is intuitive considering land scarcity. The importance of soil quality as indicated by average precipitation is also supported by the data.

Table 4. Estimation results (dependent variable = the log of agricultural output per/ha)

Variables	Fixed effects model				Hausman-Taylor model			
	Specification 1		Specification 2		Specification 1		Specification 2	
	Coeff.	Std.Err	Coeff.	Std.Err.	Coeff.	Std.Err	Coeff.	Std.Err.
Time varying exogenous var.								
Average precipitation	0.027**	0.011	0.026**	0.011	0.026***	0.010	0.026**	0.011
Average max temp	0.018	0.010	0.019	0.010	0.008	0.007	0.010	0.008

[4] The Durbin-Wu-Hausman test statistic indicates the presence of endogeneity (p-value = 0.0023) when district fixed effects are excluded in the estimations. The corresponding test based on the Hausman-Taylor estimations results in a p-value of around 0.256 suggesting that the latter is a more consistent estimator.

Time variant endogenous var.								
R_Pop density (ln)	1.229***	0.150	1.306***	0.152	1.195***	0.148	1.274***	0.151
Harvested area (ln)	1.758***	0.161	1.880***	0.166	1.729***	0.160	1.853***	0.165
Specialization (HHI_{it})	0.267***	0.046	-	-	0.268***	0.047	-	-
Diversification (H)	-	-	0.00001***	2.58e-06	-	-	0.00001***	2.58e-06
t	-0.053**	0.014	-0.053***	0.013	-0.053***	0,014	-0.053***	0.139
Constant	-10.927***	1.957	-12.973**	2.017	-11.333***	2.016	-13.498***	2.088
N	420		420		420		420	
N of groups	28		28		28		28	
R square (within)	0.310		0.296		-		-	
F	28.97***		27.10***		-		-	
Wald chi2	-		-		180.61		167.64	

***, ** indicate significance at the 1 and 5 % levels.

4.2. Scale- and complementary effects

In order to assign the importance of the individual crops and to obtain a more flexible specification which allows for scale effects among the inputs, Equation 1 is re-estimated including the crop shares and their squared covariates. These results are presented in Table 5.

The coefficient of beans and cassava are positive and statistically significant (specification 1) indicating that increases in the land devoted to the cultivation of these crops have a positive influence on aggregate (district) agricultural productivity. While the effects that apply to most of the other crops cannot be statistically differentiated from zero, the influence of increased land use devoted to sorghum, sweet potatoes and soybeans show negative effects. Results also indicate the presence of non-linear scale effects in the cultivation of bananas and sweet potatoes (specification 2). The squared covariates included to capture the presence of non-linear scale-effects are both positive and statistically significant for beans and cassava, indicating that the productivity effects of cultivating such crops turn to positive once the production volume exceeds a certain size. Turning to complementariness among the crops (Table 4). Equation 1 is re-estimated for the six major crops using their values of the log of kg/ha as dependent variables. Results indicate that there exist both negative and positive complementarity effects. The cultivation of beans and cassava is shown to give rise to positive complementary effects for several crops. The production of beans (per/ha) is shown to be positively related to increases in land use devoted to the cultivation of bananas, cassava, irish potatoes and sweet potatoes and the production of cassava is shown to be positively related to increases in land use devoted to the cultivation of maize and sweet potatoes.

Table 5. Estimation results (dependent variable = the log of agricultural output per/ha)

Variables	Fixed effects model				Hausman-Taylor model	
	Specification 1		Specification 2		Specification 2	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Time variant exogenous var.						
Average precipitation	0.032**	0.011	0.032**	0.010	0.033**	0.009
Average temperature	0.026**	0.009	0.022**	0.009	0.014	0.007
Time variant endogenous var.						
R_Pop density (ln)	0.662***	0.160	0.724***	0.165	0.672***	0.166
Harvested area (ln)	1.232***	0.174	1.328***	0.178	1.266***	0.180
Beans	0.814***	0.170	0.939	0.533	0.941**	0.152
Banana	-0.188	0.241	-1.741**	0.575	-1.805**	0.574
Maize	-0.172	0.191	-0.455	0.537	-0.381	0.539
Cassava	0.788***	0.214	-0.026	0.396	-0.016	0.416
Sorghum	-0.761***	0.186	-0.379	0.435	-0.625	0.459
Irish potatoes	-0.038	0.297	-0.277	0.576	-0.171	0.588
Sweet potatoes	-1.030**	0.364	-2.824**	1.037	-2.686**	1.067
Soybeans	-1.926***	0.501	-	-	-	-
Peas	-0.027	0.567	-	-	-	-
Wheat	-0.279	0.474	-	-	-	-
Yam and Toro	-1.643	0.946	-	-	-	-
Groundnuts	-1.660	0.979	-	-	-	-
Rice	-1.161	1.304	-	-	-	-
Vegetables and Fruits	-0.554	0.504	-	-	-	-
Beans^2	-	-	0.533	0.940	-0.374	0.939

Banana^2	-	-	2.935**	0.961	3.027**	0.960
Maize^2	-	-	0.261	0.537	0.206	1.426
Cassava^2	-	-	0.968	0.557	1.040**	0.230
Sorghum^2	-	-	-2.060	0.576	-2.165	1.761
Irish potatoes ^2	-	-	0.064	0.576	-0.057	1.499
Sweet potatoes^2	-	-	9.427**	5.509	9.338	5.507
t	-0.046**	0.013	-0.042**	0.013	-0.042**	0.013
Constant	-4.844**	2.092	-5.574**	2.121	-5.236**	2.183
N	420		420		420	
N of groups	28		28		28	
R sq. (within)	0.433		0.310		-	
Wald chi2	-		-		312.20***	

***, ** indicate significance at the 1 and 5 % levels. Minor crops are excluded from the estimation of the second specification to avoid problems with multicollinearity

Table 6. Estimation results by main crops

Variables	Hausman-Taylor model											
	Beans ln(kg/ha)		Bananas ln(kg/ha)		Maize ln(kg/ha)		Cassava ln(kg/ha)		Irish potatoes ln(kg(ha)		Sweet potatoes ln(kg/ha)	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Time variant exog. var.												
Average precipitation	-0.018	0.024	0.013	0.011	0.047**	0.021	0.072**	0.024	0.049**	0.022	0.057**	0.018
Average temperature	-0.017	0.017	0.021**	0.009	0.010	0.017	0.034	0.018	0.014	0.017	0.016	0.012
Time variant end.var.												
R_Pop density (ln)	1.947***	0.381	-0.048	0.184	2.890***	0.330	1.188**	0.397	-0.495	0.367	0.391	0.301
Harvested area (ln)	3.225***	0.415	0.265	0.196	3.702***	0.356	2.096***	0.432	-0.354	0.396	0.597**	0.335
Crop diversification	1.17e-04	6.78e-06	1.23e-04***	3.31e-06	-1.31e-06	5.91e-06	0.000	7.39e-06	0.000	6.61e-06	1.97e-04**	5.76e-06
Beans	-	-	0.704**	0.202	0.151	0.366	1.098**	0.446	1.146***	0.400	2.068***	0.352
Banana	-0.300	0.587	-	-	-0.264	0.501	0.078	0.614	-0.826	0.571	0.028	0.485
Maize	0.802	0.472	-0.197	0.223	-	-	-0.743	0.489	0.460	0.446	-0.104	0.385
Cassava	0.756	0.513	0.006	0.245	2.071***	0.438	-	-	0.021	0.485	0.818**	0.422
Sorghum	-0.086	0.449	-0.537**	0.220	-1.775***	0.344	-1.288**	0.481	-0.533	0.427	-0.806**	0.371
Irish potatoes	-0.756	0.698	-0.542	0.342	-0.772	0.610	1.352**	0.759	-	-	0.604	0.576
Sweet potatoes	0.100	0.884	-0.402	0.422	-2.912***	0.751	-1.379	0.923	0.620	0.841	-	-
Soybeans	-0.378	1.202	-0.215	0.575	-0.069	1.028	0.212	1.260	-2.143	1.145	-1.480	0.986
Peas	1.527	1.359	0.380	0.650	1.115	1.165	-0.391	1.418	-0.051	1.285	-1.670	1.114
Wheat	-0.841	1.104	-0.336	0.540	0.333	0.961	-0.022	1.155	0.662	1.045	1.259	0.917

Yam and Toro	0.704	2.276	0.561	1.088	-4.712**	1.924	-0.846	2.374	-3.271	2.173	-2.974	1.872
Groundnuts	-0.035	2.352	-3.433**	1.115	-1.961	2.013	-1.154	2.418	-1.900	2.247	-0.311	1.930
Rice	-2.252	3.120	-0.076	1.490	-5.181	2.676	2.877	3.296	-1.474	2.962	-1.225	2.602
Vegetables and Fruits	-2.239	1.192	-0.336	0.565	-0.352	1.033	0.031	1.217	-0.949	1.148	-2.395**	0.986
t	0.083**	0.031	0.022	0.015	0.112***	0.027	-0.185**	0.033	0.011	0.030	0.004	0.026
Constant	-31.590**	5.238	5.582**	2.510	-40.819***	4.548	-16.674	5.417	13.070**	5.013	-0.059	4.117
N	420		420		420		420		420		420	
N of groups	28		28		28		28		28		28	
Wald chi2	127.72***		111.23***		405.14***		135.05***		92.61***		126.01***	

***, ** indicate significance at the 1 and 5 % levels.

CONCLUSIONS AND RECOMMENDATIONS

This study examined the factors that determine agricultural productivity growth in Rwanda, distinguishing between the effects of crop specialization and crop diversification. The theoretical framework takes an eclectic approach and hypotheses are derived from different theoretical frameworks and tested by estimating a Cobb-Douglas production function using panel data that include 15 time periods, covering the years 2006-2013 and their corresponding growing seasons. The importance of both conventional inputs and measures of specialization and diversification in explaining agricultural productivity growth is supported by the data. Results indicate that there are significant differences in agricultural productivity among Rwandan districts that can be attributed to differences as measured by their degree of labor intensity, land supply and crop composition. The model estimations suggest that both crop specialization and crops diversification is positively associated with growth in agricultural productivity during the studied time period. Furthermore, both the supply of harvested land and the ratio of population to harvested land, thought to reflect land and labor intensity, are shown to be positively associated with growth in productivity. Estimating the model across the main crops to indicate complementary effects shows that it is profoundly the cultivation of beans and cassava that result in such effects.

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