Crop diversification, downside risk exposure, and crop production in the Niger basin of Benin

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Abstract
This paper investigates the extent to which crop diversification affects farm productivity and production risk in the Niger basin of Benin. The paper relies on a moment-based approach, and estimates a stochastic production function which captures the effects of crop diversification on the mean, the variance, and the skewness by controlling for the unobservable heterogeneities related to institutional factors and village specific conditions. The findings reveal that diversification across crops affects positively the mean, the variance, and the skewness, with the effects being statistically significant only in the case of the mean. Thus, diversification is important in reducing the exposure to downside risk.

Key words: Cotton, diversification, downside risk, Niger basin of Benin

Introduction

Agriculture in developing countries is rainfall dependent, and therefore unpredictable weather can lead to more exposure to significant production uncertainty and serious hardship (Di Falco, et al., 2011). Climate projections show that the world will face harsh climate conditions under business as usual (Hulme, et al., 2001; IPCC, 2014a; IPCC, 2014b). Crop yields are projected to primarily decrease in low latitudes, where most of the developing countries are located (Rosenzweig & Parry, 1994). The adverse effects of changing in climate conditions on crop production can result in food insecurity and famine (Di Falco & Chavas, 2009; Lokonon, 2015). The Niger basin of Benin constitutes an example of geographic areas which are predicted to face significant production uncertainty and serious hardship. The basin has experienced many floods during the last thirty years, leading to low level of crop production (MEHU; 2011).[1] However, the basin is not a drought-prone area; the most severe drought during the last forty years have occurred in 1977 and 1983.

To manage risk, farmers can rely on either ex-ante or ex-post risk management strategies. Ex-ante risk management strategies such as crop or varietal choice, and crop diversification, can lead to high level of crop production (Di Falco & Chavas, 2009; Nhemachena, et al., 2014). Crop diversification is considered as one of the means to spread production risk, instead of bearing total risk inherent to producing a single crop. Therefore, crop diversification is recognized as a measure that can help farmers to do not be severely affected by risk (Blank, 1990; Tadesse & Blank, 2003; Chavas, 2011). It is rare to find farmers growing a single crop in the Niger basin of Benin. Thus, one can question the effective role of growing more than a single crop in risk management.

Three types of production diversification are used by farmers namely diversification across products (a strategy derived from portfolio theory developed in the stock market) which is the most common, diversification across locations, and cultivar diversification (Tadesse & Blank, 2003). The diversification across products consists of growing more than one commodity, and aims to reduce the variance inherent to sale revenues. Diversification across locations is relative

[1] The most severe floods have been recorded in 1988, 1997, 1998, and 2010.

to operating more than a single parcel separated geographically to address yield variability due to weather conditions, and this strategy can be practiced by farmers producing only one crop. Cultivar diversification is characterized by temporal diversification combined with aspects of each of the other two diversification strategies.

This paper aims to investigate the effects of diversification across products on farm productivity and production risk in the Niger basin of Benin. Indeed, diversification across crops is described by farmers as an easily implemented and effective strategy in revenue risk management (Blank, 1990; Tadesse & Blank, 2003). Thus, the extent to which diversification across products affects farm productivity and production risk relative to a given important crop is worth investigating for policy implications related to reducing the exposure to downside risk. Following Antle (1983), Di Falco & Chavas (2009), and Di Falco & Veronesi (2014), the analyses rely on a moment-based specification of the stochastic production function. Thus, the analyses capture the effects of crop diversification on the mean, the variance, and the skewness of crop production. Although the investigation of the mean and the variance effects is standard (e.g., Just & Pope, 1979), it is not possible to distinguish between unexpected bad and good events based on the variance, and therefore considering skewness in risk analysis seems to be important (Di Falco & Chavas, 2009). On that basis, a reduction in downside risk exposure is characterized by an increase in skewness of crop yields (Di Falco & Chavas, 2009; Di Falco & Veronesi, 2014).

Previous papers investigated the extent to which adaptation measures contribute to reducing climate change effects on crop productivity (e.g., Di Falco, et al., 2011) by relying on the endogenous switching regression. Di Falco & Chavas (2009) investigated how crop genetic diversity contributes to farm productivity and affects risk exposure in the Highlands of Ethiopia. Di Falco & Veronesi (2014) combined the moment-based specification of the stochastic production function with the endogenous switching regression approach to shed light on the impact of climate change adaptation on farm households' downside risk exposure in the Nile Basin of Ethiopia. The paper contributes to the existing literature by analyzing how crop diversification contributes to productivity and influences downside risk exposure following Di Falco & Chavas (2009). Two research questions are investigated in the paper: (i) How does crop diversification affect production level of a given crop?; and (ii) What is the relative importance of diversification in reducing the probability of crop failure?

Farmers in the Niger basin of Benin are differently affected by climate change, depending on their types and agro-ecological conditions (Lokonon, et al., 2015). On that basis, three challenges have to be accounted for in the analyses (Di Falco & Chavas, 2009). Thus, it is necessary to investigate to which extent farm-specific agro-ecological and village settings influence productivity and risk exposure. Moreover, controlling for the effects of unobservable factors, such as disparities across villages due to location and institutional factors is required. Furthermore, the interplay between the farm-specific characteristics which are under farmers' control versus those affecting risk exposure need to be analyzed.

The paper relies on a refined econometric estimation of the production process under risk. Like previous papers (e.g., Di Falco & Chavas, 2009), special attention is given to the effects of local environmental conditions and managerial decisions, because controlling for such effects is important in order to reduce the potential biases arising from omitted variables. Therefore, this provides a framework to study the influence on productivity of crop diversification, with implications for risk management.

The paper proceeds as follows. Section 2 describes the material and the methods used. Section 3 presents the results along with discussion, and section 4 concludes by pointing out directions for future research.

Material and methods

Methods

In this paragraph an econometric model of crop diversification, crop production, and risk exposure is specified. Following Antle (1983) and like Di Falco & Chavas (2009) and Di Falco & Veronesi (2014), this paper relies on a moment-based approach of the stochastic production function. Thus, risk exposure is investigated through the moments of the production function. Let $y = g(x, w)$ represent the well-behaved stochastic production function of a risk averse farm household producing output y using inputs x under risk. The vector w is composed of random variables which are not under control of the farm household (e.g., climate variables). Thus, the econometric specification of the production function is:

$$g(x, w) = f_1(x, \beta_1) + \mu \quad (1)$$

where $f_1(x, \beta_1) \equiv E[g(x, w)]$ represents the mean of $g(x, w)$, and $\mu = g(x, w) - f_1(x, \beta_1)$ is a random variable with mean 0. The distribution of μ is exogenous to farmers' actions, and assuming normality assumptions regarding μ is not necessary in estimating the production function (Di Falco & Veronesi, 2014).[2] The higher moments of the production function are given by:

$$E\{[g(x, w) - f_1(x, \beta_1)]^k | x\} = f_k(x, \beta_k), \;\; k = 2, 3. \quad (2)$$

Thus, $f_2(x, \beta_2)$ represents the second central moment (the variance), and $f_3(x, \beta_3)$ is the third central moment (the skewness). Therefore, it is possible to provide a flexible representation of the extent to which inputs x affect the distribution of output under production uncertainty (Di Falco & Chavas, 2009; Di Falco & Veronesi, 2014). The approach enables to investigate downside risk exposure through the third moment (skewness). An increase in downside risk is characterized by an increase in the asymmetry (or skewness) of the risk distribution toward low outcome, holding both the mean and variance constant (Menezes, et al., 1980; Di Falco & Chavas, 2009; Di Falco & Veronesi, 2014).

[2] Di Falco & Veronesi (2014) argued that in the case of normally distributed errors, the distribution would be symmetric by construction, and the third central moment would be zero.

In the estimations the variables measured as deviations from their village means are used following Barrett *et al.* (2004) and Di Falco & Chavas (2009). Thus, it is possible to control for the unobservable disparities related to institutional factors and village specific conditions.

Data and Variables used

This paper uses survey data which is relative to the 2012/2013 agricultural year, collected in the Niger basin of Benin which covers 37.74% of Benin (Lokonon, 2015; Lokonon, et al., 2015). The sampling followed a three-stage approach. At the first stage, seven communes were randomly selected within the four agro-ecological zones by relying on their number of farm households. At the second stage, villages were randomly chosen within the selected communes. At the third stage, farm households were randomly selected within the chosen villages. It is worth noting that the basin covers normally five agro-ecological zones, and the fifth was left aside because only one of its communes is within the basin. At the end of process, 545 farm households were surveyed. In the dataset, a total of 219 farm households produced cotton, so 40.18%. Therefore, it is this subset of the 545 observations that is used to estimate the stochastic production function for cotton in this paper. Cotton is selected because it constitutes an important source of cash income for farm households (Lokonon, 2015). It is also the main export product of Benin. Moreover, Lokonon, et al., (2015) found that farm households that produce cotton will be the most affected by climate shocks, ceteris paribus.

The variables used, and their descriptive statistics are reported in Table 1. In this paper, diversification is captured by the Simpson diversity index (D) defined as (Meng, et al., 1999):

$$D = 1 - \sum p_i^2 \qquad (3)$$

where p_i is the area share occupied by ith crop production. The Simpson diversity index measures the richness (the number of species encountered in a given sampling effort) and the evenness (combination the proportional representation with the number of species) (Meng, et al., 1999). The larger is the Simpson diversity index, the greater is the number of crops grown by a given farm household. It is worth noting that the Simpson diversity index is equal to one minus the Herfindahl index used in the industrial organization literature, and is applied by previous papers (Smale, et al., 1998; Meng, et al., 1999). Apart from the diversity index, three categories of regressors are used: (i) conventional inputs (land, labor, cattle, fertilizer, and insecticide); (ii) variable related to environment and soil characteristics (fertility); (iii) managerial variables (years of experience in agriculture, and land in other crops). Fertility is computed by relying on farm perception of land fertility. In the questionnaire, farmers were asked to rank the fertility of each type of soil as very fertile, fertile, little bit fertile, and non-fertile. Thus, the sizes of the soils ranked as very fertile and fertile are sum up and the sum is divided by the total land to obtain the share of the land classified as fertile. On average, 43.59% of the total land are classified as fertile.

Table 1. Variables' list, definitions, and descriptive statistics

Variable	Definition	Mean	Standard	Minimum	Maximum

			Deviation		
Cotton	Quantity of cotton harvested in kilograms	3094.70	3605.04	200	29000
Diversification	Simpson diversity index	0.67	0.12	0	0.85
Land	Land for cotton in ha	3.05	3.02	0.25	26
NPK	Fertilizer use in kilograms	118.98	71.17	0	450
Insecticide	Insecticide use in litters	2.92	2.85	0	15
Cattle	Number of cattle	6.14	28.97	0	400
Family size	Adjusted family size capturing labor in man-equivalent (0.75 and 0.5 for women and children, respectively)	5.97	3.51	1.75	19.75
Land in other crops	Land allocated to other crops in ha	5.86	3.83	0	18.5
Fertility	Share of fertile land (%)	43.59	49.40	0	100
Fertility*fertility	Squared of fertility	4329.11	4949.58	0	10000
Experience	Number of years in agriculture	23.11	14.60	2	75
Land*experience	Interaction between land and experience	76.74	115.04	2	1040

On average, cotton production occupied 3.05 ha among cotton producers in the basin. In terms of harvested output, on average, the farm households harvested 3,094.7 kilograms of cotton at the end of the targeted campaign. The average land used for the other crops by the farm households amounted to 5.86 ha. Although, fertilizer and pesticide related to cotton production is managed through extension officers, all the farmers did not applied either fertilizer or insecticide. Indeed, 89.95% and 73.97% of farmers applied fertilizer and insecticide, respectively, which is quite high. It is worth noting that there are farm households that reduced the quantity of fertilizer to be applied to cotton and have applied it to other crops such as maize as it is not possible for them to benefit for fertilizer credit outside of the cotton system. Labor does not appear to be a limiting factor in the basin, because the average adjusted family size (in man-equivalent) used as proxy of labor is 5.86. On average, 23.11 years were spent in agriculture with a minimum of 2 years and a maximum of 75 years.

Estimation procedure

First, two functional specifications of the mean function were explored. They include the quadratic, an alternative of the quadratic in which the dependent variable is in natural logarithm. The choice of the appropriate functional specification was based on both the Akaike's Information Criterion (AIC), and the Bayesian Information Criterion (BIC). The AIC was 3,979.0 and 459.36 for the quadratic, and the second functional specification, respectively. The corresponding BIC was 4019.6 and 500.03, respectively. Both the AIC and the BIC had the minimum values for the second specification. Therefore, in the mean function, the dependent variable is expressed in natural logarithm.[3] On that basis, it is required to carefully compute the

[3] It is worth noting that as the skewness displays negative values for some observations, the quadratic functional form was preferred for both the variance, and the skewness.

second and the third central moments after estimating the mean. The functional specification of the mean is given as:

$$log(y) = h_1(x, \delta_1) + \varphi \quad (4)$$

Thus,

$$\widehat{log(y)} = h_1(x, \delta_1) \quad (5)$$

and

$$\hat{y} = e^{h_1(x,\delta_1)}. \quad (6)$$

Therefore, the second and the third central moments are given by:

$$E\left\{\left[g(x, w) - e^{h_1(x,\delta_1)}\right]^k |x\right\} \equiv f_k(x, \beta_k), \ \ k = 2, 3. \quad (7)$$

As the specifications may be subject to endogeneity bias, the paper accounts for that. Endogeneity bias would occur if a subset of the regressors were correlated with the error term. In the presence of endogeneity, estimating the mean, the variance, and the skewness will be biased. However, as the variables used are expressed in deviation from village means, village-specific unobserved heterogeneity are removed leading to a possible reduction of the endogeneity (Hsiao, 1986; Di Falco & Chavas, 2009). Endogeneity is investigated by applying the Durbin and Wu-Hausman tests (Cameron & Trivedi, 2005). Indeed, the Simpson diversity index is assumed to be endogenous and Instrumental Variables (IV) estimators are estimated. IV estimators are consistent given valid instruments (Cameron & Trivedi, 2005). The instruments used in the estimations were household head marital status and distance from dwelling to food market in kilometers. The endogeneity tests are reported in Table 2. It appears that there is statistical evidence of endogeneity at the 10% level in the mean function with fixed effects, while there is no evidence of endogeneity in the model in levels. There is no statistical evidence of endogeneity in the variance, and the skewness equations regarding both the model in levels and the fixed effects model. Therefore, there is statistical evidence of correlation between the index and the error terms in only the mean equation.

The validity of the instruments is also tested; the instruments should be sufficiently correlated with the Simpson diversity index but uncorrelated with the error terms. The validity test was done using an F-test of the joint significance of the excluded instruments, and it revealed the rejection of the null hypothesis of weak instruments. In the case of one endogenous regressor, to be reliable the F-statistic should exceed 10 when estimating by Two-stage Least Squares (Stock, et al., 2002). The instruments are relevant. Indeed, the F-statistic found was 14.62 with ($Prob > F = 0.00$). The instruments are also tested for overidentifying restrictions using Sagan and

Basmann tests. The tests revealed that the instruments are uncorrelated with the error terms.[4] On the basis that IV estimators are consistent given valid instruments (Cameron & Trivedi, 2005), the paper relies on the IV estimators for the mean, the variance, and the skewness equations instead of estimating the three equations by the Ordinary Least Squares (OLS). As the errors are heteroskedastic, heteroskedastic-consistent standard errors are estimated. There is no evidence of multicolinearity in the functions, because all the Variance Inflation Factors (VIF) are below 2.

Table 2. Durbin and Wu-Hausman endogeneity tests

	Model in levels		**Model with fixed effects**	
	Durbin Test	Wu-Hausman Test	Durbin Test	Wu-Hausman Test
Mean	Chi2(1)=0.2802	F(1, 206)=0.2639	Chi2(1)=3.6526	F(1, 206)=3.4940
	p-value=0.5965	p-value=0.6080	p-value=0.0560	p-value=0.0630
Variance	Chi2(1)=0.00003	F(1, 206)=0.00003	Chi2(1)=0.2858	F(1, 206)=0.2692
	p-value=0.9955	p-value=0.9957	p-value=0.5930	p-value=0.6045
Skewness	Chi2(1)=0.00001	F(1, 206)=0.00001	Chi2(1)=0.4191	F(1, 206)=0.3949
	p-value=0.9973	p-value=0.9974	p-value=0.5174	p-value=0.5304

Results

Table 3 reports the econometric results. The effect of diversification on production is positive and significant at the 10% level. This finding is in line with those found elsewhere (e.g., Di Falco, et al., 2011). This finding show that increasing the number of crops grown has a positive effect on cotton production. Land in cotton production and in other crop production and fertilizer have positive and statistically significant impacts on the mean. The elasticity of production is 0.0152, 0.0013, 0.0005, and 0.0025 with respect to diversification, own land, fertilizer, and land in other crops, respectively. Although the signs of the elasticities associated to the remaining variables are consistent with the literature except for experience in farming, these variables do not have statistically significant effects in the mean function. The elasticity of production with respect to experience is negative and statistically non-significant, meaning experience decreases production level, ceteris paribus. Indeed, land and fertilizer are the main production factors in terms of cotton production in the basin apart from climate variables (Lokonon, 2015).

The regression results of the variance indicate that diversification has positive effect on variability, indicating that diversity increases risk. The effect of diversification on the variance would normally be negative. It is worth noting that the variance does not distinguish between upside and downside risk (Di Falco & Chavas, 2009). Therefore, considering variance only cannot shed precise light on the effect of diversification on risk. However, the effect is not statistically significant. Fertility appears to have statistically significant quadratic effect on the variance. Indeed, variability of crop production increases with fertility up to 11.08% of fertility, and then decreases, ceteris paribus. Land and the interaction between land and experience have positive statistically significant effect on the variance. Thus, they are found to increase risk. Among the conventional inputs the number of cattle own by the farm households and family

[4] The Sagan (score) Chi2(1) amounts to 0.01, 0.95, and 0.76 with p-values of 0.92, 0.33, and 0.38, respectively. Regarding the Basmann chi2(1), it amounts to 0.01, 0.91, and 0.71 with p-values 0.92, 0.34, and 0.40, respectively.

labor appear to decrease risk. However, like for land in other crops the negative effect is statistically non-significant. Although the remaining variable have positive effect on risk, the effects are found to be statistically non-significant.

The regression results for the skewness is similar to those of the variance, except for the number of cattle which is found to increase the skewness, with the effect being statistically non-significant. Diversification is positively associated with the skewness of the output. Thus, growing more than a single crop reduces the exposure to downside risk related to crop production, although the effect is statistically non-significant. It can be seen as hedging against the risk of crop failure. This is consistent with the findings of previous papers (e.g., Di Falco & Veronesi, 2014). Land in cotton production is found to strongly reduce the exposure to downside risk, while land in other crops appears to increase the probability of crop failure. Experience in farming and the interaction between cotton acreage and experience decrease the exposure to downside risk, with the effect being statistically significant in the case of the interaction between land and experience. Fertility appears to have statistically significant quadratic effect on the skewness. Indeed, the probability of crop failure decreases with fertility up to 19.18% of fertility, and then increases, ceteris paribus. Fertilizer and insecticide decrease the exposure to downside risk, while family size increases it, with the effects being statistically non-significant.

Table 3. Mean, variance, and skewness function: Model with fixed-effects estimation results (Two-Stage Least Squares)

	Mean Function		**Variance Function**		**Skewness Function**	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Diversification	40,074.51*	21,917.17	1.64e+07	2.23e+07	4.13e+11	4.08e+11
Land	1,873.89***	362.82	6,185,007***	732,318.4	1.39e+11***	2.15e+10
NPK	17.95*	9.81	12,473.57	29,023.09	2.50e+07	5.10e+08
Insecticide	8.32	255.04	957,037	649,169.7	2.12e+10	1.33e+10
Cattle	-8.12	7.17	-1,093.23	30,585.13	7.91e+07	8.63e+08
Family size	196.30	275.19	-775,616.6	655,870.9	-1.11e+10	1.29e+10
Land in other crops	637.50***	195.53	-1,368,098	839,893.16	-4.50e+10**	2.15e+10
Fertility	4.99	11.45	37,559.25	32,593.16	9.61e+08	8.67e+08
Fertility^2	0.19	0.21	-1,695.53**	759.38	-5.01e+07**	1.98e+07
Land*Experience	0.19	11.80	612,808.2***	233,872.4	1.35e+10**	6.13e+09
Experience	-43.47	43.00	77,094.67	175,258.3	3.63e+09	4.16e+09
Constant	-219.12	399.18	9,637,048***	2,209,064	1.07e+11***	3.54e+10
		$R^2 = 0.39$		$R^2 = 0.65$		$R^2 = 0.66$
		Wald Chi2(11)=374.94		Wald Chi2(11)=452.49		Wald Chi2(11)=297.63
		Prob>chi2=0.00		Prob>chi2=0.00		Prob>chi2=0.00

***, **, *: Significance levels at the 1%, 5%, and 10% levels, respectively. The estimated coefficients and the standard errors of the mean equation are multiplied by 10,000 to ease the reading.

Conclusion

It can be exceedingly difficult to establish precisely the extent to which diversification across crops affects farm productivity and production risk. Using data from a survey conducted in the

Niger basin of Benin, the paper investigated the implications of diversification across crops to farm productivity and downside risk related to cotton production based on a moment-based approach of the stochastic production function. The mean, the variance, and the skewness are estimated and the unobservable disparities related to institutional factors and village specific conditions are controlled in the estimations. The findings reveal that diversification across crops affects positively the mean, the variance, and the skewness, with the effect being statistically significant only in the case of the mean. Thus, diversification appears to increase both the production level, and the variability of production, but it decreases the odds of crop failure (the exposure to downside risk). Therefore, diversification is important in reducing the exposure to downside risk. Crop diversification can be promoted as a risk management strategy. The paper does not shed light on the effective role of crop diversification on total revenue risk management. Future studies should explore the role of diversification across crops in total revenue risk management.

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