economies

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Quantile Analysis of the Effect of Non-Mandatory Cash Crop Production on Poverty Among Smallholder Farmers

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Abstract: Tea and coffee as traditional cash crops have been produced in Rwanda for more than six and ten decades respectively. However, new cash crops are being produced and exported, although their role in increased income and poverty reduction over traditional ones is not well understood; hence the analysis of drivers of both traditional and non-mandatory cash crop production among smallholder farmers is imperative. The study applied an experimental research design, and two strata composed of non-mandatory cash crops and traditional crop growers were used to obtain a simple random sample of 400 smallholder farmers. The study analysed the effect of cash crop production on multidimensional poverty among farmers in the Rulindo District using a quantile treatment effect. Although the poorest category of adopters places a high opportunity cost in allocating more time to off-farm activities, the poorest households that are female-headed are likely to increase multidimensional poverty once they adopt non-mandatory cash crops. Similarly, farm size does not help the poorest households to reduce poverty. Poorest households could be considered while introducing new non-mandatory cash crops because they do not help them reduce non-pecuniary poverty. Tea, coffee and food crops should be helpful among the poorest smallholder farmers.

Keywords: non-mandatory cash crops; non-pecuniary poverty; multidimensional poverty index; small-scale cash crop farming; quantile treatment effect

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Academic Editor: Ralf Fendel

Received: 13 September 2024
Revised: 4 December 2024
Accepted: 17 December 2024
Published: 29 March 2025

Citation: Uwimana, P., Obare, G. A., & Ingasia, O. A. (2025). Quantile Analysis of the Effect of Non-Mandatory Cash Crop Production on Poverty Among Smallholder Farmers. *Economies*, *13*(4), 93. https://doi.org/10.3390/economies13040093

1. Introduction

Most of the world's poor are small-scale farmers who depend on farming activities as their main source of income and Rwanda is not an exception. Various factors are causes of poverty and Gollin et al. (2014) highlighted a productivity gap in the agricultural sector compared to other non-agricultural sectors due to low human capital involved in farming activities, specifically in developing countries.

The government of Rwanda initiated a revitalization of the agricultural sector by introducing new cash crops, including cut-flowers, macadamia, chilli, sericulture, and stevia, among others, and expanding traditional cash crops (tea, coffee and pyrethrum produced for decades) to make it market-oriented agriculture, thereafter, expecting a concomitantly reduced poverty (World Bank, 2011; Ali et al., 2014) which according to Diao et al. (2010b) is less rapid among smallest landholdings compared to medium and large landholdings. Similarly, Thanichanon et al. (2018) emphasized the size of terrain as a key determinant of cash crop adoption, and if coupled with market availability, increased the producers' well-being. They also mentioned a high probability of remaining poor, if engaged in subsistence agriculture. Lipton (2005) and Mulusew et al. (2023) highlighted that despite set strategies to overcome poverty in rural areas, it was rurally more concentrated than in urban areas and more exacerbated among elderly or female-headed households of rural inhabitants who are less likely to be engaged in off-farm activities due to children care or household duties (Headey & Jayne, 2014; Alkire & Seth, 2015; Ochieng & Hepelwa, 2018; Garza-Rodriguez et al., 2021). Factors like food insecurity and price fluctuation, among others, are risks related to cash crop production and, therefore, a priori conditions to non-pecuniary poverty in rural areas (Biederlack & Rivers, 2009; Thanichanon et al., 2018). Improved well-being is a necessary condition for cash crop adoption, otherwise, even adopters may shift from cash crop to food crop production (Chen et al., 2016). The situation is exacerbated by the unevenness of technological development among two different groups of farmers, as large-scale farmers embrace high technologies whereas small-scale farmers remain with poor and less profitable technologies that leave them in multidimensional poverty (Van der Ploeg, 2012). Similarly, Vandercasteelen et al. (2016) and Ochieng and Hepelwa (2018) pointed out that technological assets like ICT assets and the availability of infrastructures are both a priori and a posteriori to the increased income and multidimensional poverty reduction among cash crop producers. Conversely, other researchers indicated that agriculture among smallholder farmers was a means to poverty alleviation, especially staple food (Diao et al., 2010a; Gong, 2020). Habiyaremye (2017) investigated the contribution of sericulture on both increased income and poverty alleviation among smallholder farmers in Rwanda and pointed out the significant effect of sericulture on increased income and reduced poverty among growers. However, the studies mentioned the existence of a small rate of adoption of that new technology among farmers. Additionally, the government of Rwanda continues to expand the production of traditional cash crops, although some growers remain poor. For example, even though Rulindo is among the districts that grow traditional cash crops, it was among the three poorest Districts in Rwanda in 2017 with a poverty level of 54.2% and extreme poverty of 23.2%.

These above-mentioned studies show varied findings on the role of farming activities on poverty alleviation, impulsively pushed the researcher to unearth the contribution of some non-mandatory cash crop production on multi-dimensional poverty reduction among small-scale farmers. Thus, because previous studies did not ponder on the role of these specific crops on multi-dimensional poverty reduction using a quantile regression method, the study was of paramount importance. This study is grounded on the theory of utility maximization. The utility theory was used to describe the responsiveness of farmers to new technology (non-mandatory cash crop adoption in this study). A farmer switches from traditional crops to non-mandatory cash crops only if the utility achieved from the latter is higher than from the former (Awotide et al., 2016). The conceptual framework used in the study emphases on the link between characteristics of the operating farm, characteristics of the operating farmer, institutional and policy factors, information access, household' risk perception and adoption of new cash crops. It is based on Winklemann and Secretariat (1998) adapted in Kerr and Kolavalli (1999) that relates adoption of new technology along with other moderating variables like accessibility to information, expectations of input use to poverty reduction through adopters income. Poorest households that adopt non-mandatory cash crops did not significantly reduce non-pecuniary poverty as opposed to traditional crops like tea, coffee and food crops that help them reduce non-pecuniary poverty.

2. Methodology

2.1. Study Area

Rwanda is in Central Africa, just in the south of the equator between latitudes 1°04′ and 2°51′ south and between longitudes 28°45′ and 31°15′ east. It has a surface area of 26.338 km^2 with 500 inhabitants per km^2 for the physical density (Government of Rwanda, 2018, National Institute of Statistics of Rwanda (NISR) (2021)). Rulindo District spans 566.7 km^2 and includes 17 sectors, 71 cells, and 494 villages[1]. The key agricultural challenges in the district include low yields, limited distribution and marketing, soil acidity, climate change, insufficient research, minimal private sector involvement, and high loan interest rates. The crop commercialization rate in Rulindo is 17.7%, below the national average of 20.9%.

2.2. Research Design

This study used an experimental design to examine how non-mandatory cash crop production affects multi-dimensional poverty among smallholder farmers. Two treatment groups were both non-mandatory cash and traditional crop producers. The design was chosen based on the fact that respondents were administered three series of lottery to elicit their risk attitude, and factors could be manipulated to depict their effects on predictands (Bordens & Abbott, 2011; Kibet et al., 2018). In addition, we administered a semi-structured questionnaire to respondents to collect the necessary information for this study. Additionally, we grounded the study on a theory-testing approach.

2.3. Sampling Procedure

The study was anchored on multi-stage sampling where the target population of 62,000 agricultural households in Rulindo District were considered. The following stage was the establishment of two strata composed of 200 non-mandatory cash crops and 200 traditional crops smallholder farmers, for a whole sample of 400 respondents determined using the Yamane (1967) formula. Given the fact that the proportion of households involved in non-mandatory and traditional crop production was unknown a priori, a proportion of 0.5 for each stratum was assumed to compute the subsample size using Kothari's (2004) formula.

At the sector level, proportionate and stratified sampling procedures were used across non-mandatory and traditional crop producers. At the household level, random sampling was used to obtain respondents, and they were administered a semi-structured questionnaire to elicit their response on various questions. A subsample of 120 which is 30 per cent of the whole sample, and proportionally composed of growers and non-growers of non-mandatory cash crops was obtained using systematic random sampling. The subsample was subjected to a quasi-experiment to elicit their risk attitude.

2.4. Model Specification

This study used cross-sectional data and estimated specific econometric models to elicit the effect of non-mandatory cash crop production on poverty among smallholder farmers. The following linear model depicts the relationship between the Multi-dimensional Poverty Index (MPI), a proxy of non-pecuniary poverty, as a dependent variable and other independent variables.

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij} + \beta_3 x_{ij} C_{ij} + \cdots + \beta_{k-1} x_{ij} + \beta_k x_{ij} + \varepsilon_{ij} \tag{1}$$

where. $\beta_{i's}$ represent vectors of regression coefficients of factors influencing MPI; C_j is crop j; I is farmer I; and x_j denotes a vector of independent variables.

In the estimation of this model, the impact of production indicates the units by which the MPI increases or decreases with each unit increase in the use of a particular explanatory variable.

Quantile Regression Model

Following Koenker and Hallock (2001) observations with missing data from any variable were dropped out of the analysis. A quantile regression model is chosen because it can depict the effect of a predictor (with varying coefficients) at different levels of the explained variable. Interest was put on the lowest and highest extremes of the distribution of poverty. This approach provides an advantage over linear regressions, which have a constant coefficient for predictors. Both income (pecuniary) and non-pecuniary factors, such as education, family health, and housing conditions, are considered as poverty dimensions. A multidimensional poverty index (MPI) was computed following Alkire and Seth (2015).

To obtain the estimates of the conditional quantile function, absolute values are replaced by $\rho(.)$ by using the following equation:

$$\min_{\beta\in\mathbb{R}}\sum\rho_{\tau}(y_i-\xi(x_i,\beta)) \tag{2}$$

where $\rho(.)$ is the tilted absolute value function that yields the τ^{th} quantile of the sample as its solution.

The method is useful to compare the relative impact of new cash crops growing on different groups, say, women, and non-adopters among others. The study was interested in assessing the impacts of growing non-mandatory cash crops among other factors on the poverty levels of households.

A Quantile Treatment Effect Model (QTE) also called the Instrumental Variable Quantile Regression Model was used to account for endogeneity, thus:

$$A_{hh} = \theta accinf_{hh} + X'_{hh}\beta + \varepsilon \tag{3}$$

where X is a vector of explanatory variables affecting income and access to information is used as an instrument. Access to information is unrelated to income and is a dummy variable.

$$\ln_{Y_{hh}} = \alpha A_{hh} + X'_{hh}\beta + \varepsilon \tag{4}$$

Let Equations (3) and (4) represent standard normal models. The τ^{th} quantile regression estimator $\hat{\beta_\tau}$ is attained by minimizing the loss function subject to the true $\beta(\tau)$ as:

$$\hat{\beta}(\tau) = \underset{\beta\in\Re^p}{\operatorname{argmin}}\left[\sum_{i:\ y\geq x_i'\beta}^{n}\tau|y_i-x_i'\beta| + \sum_{i:\ y<x_i'\beta}^{n}(1-\tau)|y_i-x_i'\beta|\right] = \underset{\beta\in\Re^p}{\operatorname{argmin}}\sum_{i=1}^{n}\rho_\tau(y_i-x_i'\beta) \tag{5}$$

The use of quantile regression permits to estimate $\beta(\tau)$ for any quantile τ such that $\in$ (0,1), meaning, the relationship between an independent X and any quantile $\in$ the distribution of Y. The endogeneity problem was addressed by using QTE where the estimated conditional quantile model is:

$$Q_{lnY_{hh}|X}(\tau) = \alpha(\tau)A_{hh} + X'_{hh}\beta(\tau) \tag{6}$$

To measure non-pecuniary poverty effects of new cash crop adoption, education, health, and housing conditions were used as indicators. Following (Zuluaga Diaz, 2010; Alkire & Seth, 2015), and making reference to Table A1 in the Appendix A, each household seeks to maximize the utility of the non-pecuniary amenities, assuming equal weight of their components in defining their indices according to the following utility equation

$$\mathrm{MPI} = \alpha + \beta A_{hh} + \gamma lnY_{hh} + X'_{hh}\varnothing + \nu \quad (7)$$

where MPI denotes non-pecuniary dimensions of poverty which comprises of education, health, and housing condition index outcomes. On the Right Hand Side (RHS) of the equation A_{hh} is the adoption of cash crops, lnY_{hh} is household income and all other characteristics of the households are represented by the vector X'_{hh}.

The focus was on the effect of adoption and income on households' non-pecuniary poverty because both induce differences in poverty levels among households. Since both the adoption and income variables are endogenous, the error term is $\nu = \nu + \varepsilon$, comprises the sum of an exogenous component and the component of unobserved factors that are related to income and adoption. The access to information variable is used as an instrument because it influences adoption but not non-pecuniary poverty, directly. The income variable is instrumented by using the involvement of a farmer in off-farm activities or not, variable. Although the instrument may be highly correlated with MPI, the falsification test gives results show that the off-farm activities opportunity variable is a suitable instrument. The availability of off-farm activities opportunities affects the income but does not influence the MPI.

3. Results and Discussion

To establish the effect of non-mandatory cash crop adoption on poverty among smallholder farmers, a quantile treatment effect was used, and Table 1 contains results that relate to non-pecuniary returns captured in as MPI with some predictors. Adoption is considered as a key factor in the specific analysis. The MPI which reflects for the level of deprivation scores, with the lowest quantiles to representing the least poor households, whereas the highest quantile represents the poorest households.

Table 1. Effect of non-mandatory cash crops adoption on non-pecuniary poverty.

MPI	Coef.	St. Err.	t-Value	*p*-Value	[95% Conf	Interval]	Sig
q10							
Income	−0.001	0.019	−0.03	0.972	−0.037	0.036	
Farm size	−0.012	0.009	−1.36	0.174	−0.03	0.005	
Market accessibility	−0.034	0.014	−2.51	0.012	−0.061	−0.007	**
age	−0.004	0.005	−0.76	0.446	−0.013	0.006	
Age squared	0	0	1.45	0.147	0	0	
Education	−0.005	0.002	−2.22	0.027	−0.009	−0.001	**
Gender	−0.007	0.017	−0.39	0.698	−0.041	0.027	
Family size	−0.006	0.005	−1.30	0.193	−0.016	0.003	
Cooperative membership	0.001	0.025	0.06	0.956	−0.048	0.05	
experience	−0.001	0.002	−0.59	0.559	−0.004	0.002	
Off-farm revenue	−0.013	0.009	−1.36	0.176	−0.031	0.006	
Local price	0	0	−0.81	0.42	0	0	
Input efficiency expectations	−0.003	0.012	−0.26	0.796	−0.028	0.021	
Time valuation	0	0	−1.11	0.268	0	0	
adoption	0.033	0.055	0.60	0.549	−0.075	0.14	
I never take risk	−0.008	0.023	−0.35	0.723	−0.053	0.037	
I mostly do not take risk	−0.025	0.022	−1.12	0.262	−0.069	0.019	
I sometimes take risk	−0.034	0.018	−1.84	0.066	−0.069	0.002	*
In most cases, I do take risk	−0.021	0.025	−0.86	0.389	−0.07	0.027	
Constant	0.269	0.332	0.81	0.418	−0.384	0.922	

Table 1. *Cont.*

MPI	Coef.	St. Err.	t-Value	*p*-Value	[95% Conf	Interval]	Sig
q25							
Income	0.004	0.025	0.15	0.877	−0.046	0.053	
Farm size	−0.032	0.013	−2.51	0.012	−0.058	−0.007	**
Market accessibility	−0.056	0.023	−2.40	0.017	−0.101	−0.01	**
age	−0.006	0.005	−1.19	0.236	−0.016	0.004	
Age squared	0	0	1.53	0.127	0	0	
Education	−0.006	0.003	−2.06	0.04	−0.011	0	**
Gender	−0.001	0.02	−0.06	0.956	−0.04	0.037	
Family size	−0.002	0.005	−0.50	0.621	−0.012	0.007	
Cooperative membership	−0.029	0.034	−0.86	0.392	−0.096	0.038	
experience	0	0.001	0.02	0.983	−0.002	0.003	
Off-farm revenue	−0.017	0.019	−0.88	0.379	−0.055	0.021	
Local price	0	0	−0.67	0.504	0	0	
Input efficiency expectations	−0.003	0.017	−0.19	0.848	−0.037	0.03	
Time valuation	0	0	−1.23	0.221	0	0	
adoption	0.077	0.09	0.85	0.395	−0.1	0.254	
I never take risk	0.033	0.036	0.91	0.364	−0.039	0.105	
I mostly do not take risk	−0.003	0.019	−0.16	0.871	−0.041	0.034	
I sometimes take risk	0.007	0.017	0.42	0.678	−0.027	0.041	
In most cases, I do take risk	−0.001	0.022	−0.04	0.967	−0.044	0.042	
Constant	0.293	0.352	0.83	0.406	−0.399	0.985	
q50							
Income	0.002	0.044	0.05	0.957	−0.085	0.089	
Farm size	−0.025	0.017	−1.50	0.135	−0.059	0.008	
Market accessibility	−0.024	0.025	−0.94	0.346	−0.074	0.026	
age	−0.008	0.005	−1.66	0.098	−0.018	0.002	*
Age squared	0	0	1.68	0.094	0	0	*
Education	−0.009	0.004	−2.25	0.025	−0.017	−0.001	**
Gender	−0.004	0.031	−0.12	0.906	−0.064	0.057	
Family size	−0.001	0.004	−0.34	0.735	−0.01	0.007	
Cooperative membership	−0.019	0.033	−0.58	0.561	−0.085	0.046	
experience	0	0.001	−0.30	0.762	−0.003	0.002	
Off-farm revenue	−0.038	0.029	−1.33	0.183	−0.095	0.018	
Local price	0	0	0.39	0.697	0	0	
Input efficiency expectations	−0.002	0.013	−0.15	0.882	−0.028	0.024	
Time valuation	0	0	−1.32	0.189	0	0	
adoption	−0.076	0.099	−0.76	0.446	−0.27	0.119	
I never take risk	0.061	0.043	1.41	0.159	−0.024	0.146	
I mostly do not take risk	−0.004	0.025	−0.14	0.889	−0.054	0.047	
I sometimes take risk	0.008	0.024	0.34	0.736	−0.039	0.055	
In most cases, I do take risk	0.005	0.034	0.14	0.89	−0.062	0.072	
Constant	0.522	0.623	0.84	0.403	−0.704	1.747	
q75							
Income	0.011	0.026	0.41	0.685	−0.04	0.061	
Farm size	0.014	0.021	0.67	0.504	−0.027	0.054	
Market accessibility	−0.018	0.028	−0.66	0.513	−0.073	0.036	
age	−0.015	0.009	−1.73	0.084	−0.032	0.002	*
Age squared	0	0	1.51	0.132	0	0	
Education	−0.013	0.005	−2.60	0.01	−0.022	−0.003	***
Gender	0.034	0.033	1.04	0.298	−0.03	0.098	
Family size	0.007	0.006	1.16	0.245	−0.005	0.02	
Cooperative membership	0.015	0.049	0.31	0.754	−0.081	0.112	
experience	0.001	0.001	0.69	0.491	−0.002	0.004	

Table 1. *Cont.*

MPI	Coef.	St. Err.	t-Value	*p*-Value	[95% Conf	Interval]	Sig
Off-farm revenue	−0.033	0.035	−0.94	0.347	−0.102	0.036	
Local price	0	0	0.72	0.473	0	0	
Input efficiency expectations	−0.027	0.017	−1.65	0.101	−0.06	0.005	
Time valuation	0	0	−2.15	0.032	0	0	**
adoption	−0.118	0.104	−1.14	0.257	−0.323	0.086	
I never take risk	0.078	0.041	1.91	0.057	−0.002	0.159	*
I mostly do not take risk	0.065	0.037	1.77	0.077	−0.007	0.137	*
I sometimes take risk	0.074	0.034	2.17	0.031	0.007	0.142	**
In most cases, I do take risk	0.044	0.032	1.36	0.173	−0.019	0.107	
Constant	0.624	0.371	1.68	0.094	−0.106	1.355	*
q90							
Income	0.023	0.05	0.45	0.651	−0.075	0.12	
Farm size	0.01	0.022	0.45	0.656	−0.033	0.052	
Market accessibility	−0.014	0.037	−0.38	0.702	−0.088	0.059	
age	−0.021	0.011	−2.02	0.044	−0.042	−0.001	**
Age squared	0	0	2.25	0.025	0	0	**
Education	−0.009	0.006	−1.46	0.146	−0.021	0.003	
Gender	0.041	0.04	1.01	0.314	−0.039	0.12	
Family size	0.013	0.009	1.53	0.127	−0.004	0.03	
Cooperative membership	−0.017	0.062	−0.27	0.785	−0.139	0.105	
experience	0.001	0.002	0.49	0.628	−0.003	0.005	
Off-farm revenue	0.001	0.04	0.03	0.973	−0.078	0.081	
Local price	0	0	−0.13	0.899	0	0	
Input efficiency expectations	−0.033	0.021	−1.59	0.112	−0.074	0.008	
Time valuation	0	0	−2.57	0.011	0	0	**
adoption	−0.015	0.153	−0.10	0.924	−0.316	0.286	
I never take risk	0.118	0.054	2.17	0.031	0.011	0.225	**
I mostly do not take risk	0.059	0.045	1.32	0.187	−0.029	0.148	
I sometimes take risk	0.077	0.051	1.51	0.131	−0.023	0.177	
In most cases, I do take risk	0.026	0.032	0.80	0.424	−0.038	0.09	
Constant	0.6	0.722	0.83	0.407	−0.82	2.021	
Mean dependent var	0.231			SD dependent var		0.141	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Breusch-Pagan/Cook-Weisberg test for heteroskedasticity with a null hypothesis of constant variance was conducted and showed the presence of heteroskedasticity. $\left(\chi^2 = 25.26 | p = 0.047\right)$, suggesting that a quantile regression was more robust and, therefore, preferable to an ordinary least square regression.

From the results, adoption of non-mandatory cash crops resulted in an idiosyncratic effect on non-pecuniary poverty among smallholder farmers. Moreover, the adoption of non-mandatory cash crops worsens nonpecuniary poverty, although it has no influence on the richest groups of households within the 0.10 and 0.25 quantiles ($p = 0.549 | \beta = 0.033$ and $p = 0.395 | \beta = 0.077$). The middle and poor households' MPI is not significantly affected by the adoption of non-mandatory cash crops ($p = 0.446 | \beta = -0.076$, $p = -0.257 | \beta = -0.118$ and $p = 0.924 | \beta = -0.015$) for 0.50, 0.75 and 0.90 quantiles, respectively. This result suggests that the adoption of non-mandatory cash crops tends to benefit farmers in the poorest households bracket, as it does not influence non-pecuniary poverty.

Concerning the rich quantile of MPI, which refers to the group of households whose non-pecuniary poverty is below the median group (0.25 quantile), bigger farm size significantly reduces poverty ($p = 0.012 | \beta = -0.032$). Similarly, age significantly reduces non-pecuniary poverty in the smallholder farmers as most of the quantiles, except the very richest categories (0.10 and 0.25 quantiles). Age parameters are ($p = 0.098 \mid \beta = -0.008$, $p = 0.084 \mid \beta = -0.015$ and $p = 0.044 \mid \beta = -0.021$) for 0.50, 0.75 and 0.90 respectively. However, the age-squared variable shows the opposite effect because, in almost all the above-mentioned quantiles, it shows a positive and significant effect but with a very low magnitude. The diminishing marginal utility of non-pecuniary poverty reduction is accentuated in the quantiles of 0.50 and 0.90 which are the middle and poorest farmers' categories of non-income poverty. Their parameters are ($p = 0.094 \mid \beta = 0.000$, $p = 0.025 \mid \beta = 0.000$ for 0.50 and 0.90 quantiles respectively.

In assessing the effect of accessibility to the market on non-pecuniary poverty, rich groups of households (0.10 and 0.25 quantiles) statistically and significantly benefit from market proximity to cushion the non-pecuniary poverty effects ($p = 0.012 \mid \beta = -0.034$) and ($p = 0.017 \mid \beta = -0.056$) respectively. However, market accessibility does not have a statistically significant effect on poverty reduction among middle and poorest groups of households.

In assessing the effect of education on non-pecuniary poverty, It was found of paramount importance in non-pecuniary poverty reduction because almost all categories were proven to statistically and significantly benefit from additional years of education ($p = 0.027 \mid \beta = -0.005, p = 0.04 \mid \beta = -0.006,\ p = 0.025 \mid \beta = -0.009, p = 0.010 \mid \beta = -0.013$) for 0.1, 0.25, 0.50, 0.75 quantiles respectively. Education was not statistically significant in the 0.90. quantile (the poorest category of farmers) but with expected sign of the coefficient; ($p = 0.146 \mid \beta = -0.009$).

The risk attitude of farmers who belong to the poorest categories (0.75 and 0.90 quantiles) in terms of non-pecuniary poverty negatively affects their standards of living as those who never take risks are likely to have a high degree of non-pecuniary poverty the more they never take a risk with ($p = 0.057 \mid \beta = 0.078$) and ($p = 0.031 \mid \beta = 0.118$) respectively. Farmers' risk attitude contributes to a high degree of non-pecuniary poverty the more they mostly do not take risks or barely sometimes take risks if they belong in the poor category of farmers (0.75 quantiles). Their parameters are ($p = 0.077 \mid \beta = 0.065$) and ($p = 0.031 \mid \beta = 0.074$) respectively. Farmers who are in the richest segment (0.10) are likely to decrease non-pecuniary poverty if the more they sometimes take risk ($\beta = -0.034 \mid p = 0.066$). Those farmers with a high opportunity cost on time spent on off-farm activities have increased non-pecuniary poverty, although with very small magnitudes of coefficients ($\beta = 0.000 \mid p = 0.032, \beta = 0.000 \mid p = 0.011$) in the poor households 0.75 and 0.90 quantiles respectively.

The Gender variable did not significantly affect the level of non-pecuniary poverty among all quantiles. For example, belonging to the richest and middle categories of smallholder farmers, namely; quantile 0.10, 0.25 and 0.50 quantiles, reduce non-pecuniary poverty ($\beta = -0.007 \mid p = 0.698; \beta = -0.001 \mid p = 0.956$) and ($\beta = -0.004 \mid p = 0.906$) for quantiles 0.1, 0.25 and 0.50, respectively. Furthermore, female-headed households belonging to the poorest categories (quantiles 0.75 and 0.90), did not significantly enhance non-pecuniary poverty ($\beta = 0.034 \mid p = 0.298$ and ($\beta = 0.041 \mid p = 0.314$, respectively).

Generally, this study found farmers benefit from education to reduce non-pecuniary poverty. Educated farmers are likely to improve health and housing conditions as dimensions of MPI through affiliation of health insurance, balanced diet and good housing conditions. Generally, the study found that adopters did not reduce poverty more than non-adopters. These findings concur with those by Mulusew et al. (2023) who concluded that education generally contributes to multidimensional poverty reduction. However, the study results partly contradict Chernozhukov and Hansen (2006) and Zuluaga Diaz (2010) reported that farmers belonging to lower income quantiles are likely to benefit from education and training more than those with higher quantile index but might converge in the sense that once quantiles are taken as a proxy to unobserved ability, farmers in the lower quantiles will be likely to have good networks, improved good habits and greater valuation of health. Gollin et al. (2014) also confirmed the same as they argued that education leads to improved human capital and, thereafter reduced poverty.

The study findings on the contribution of time valuation revealed that farmers in the poor quantiles who place a high opportunity cost on the time spent in off-farm activities are likely to have increased non-pecuniary poverty. Mostly, the elderly and females are less likely to be engaged in off-farm activities, therefore having a high level of non-pecuniary poverty as Headey and Jayne (2014); Alkire and Seth (2015); Ochieng and Hepelwa (2018); Garza-Rodriguez et al. (2021) and Mulusew et al. (2023) have highlighted.

The larger the farm, the more likely a family has an opportunity to reduce non-pecuniary poverty, especially in rich households. This could be due to their ability to engage in more investments in agricultural activities. This is, however, the same as what Diao et al. (2010b) concluded showing that big holdings are more likely to reduce poverty than smaller ones. Furthermore, the study revealed that smallholder farmers who consistently avoid taking risks are more susceptible to increased non-pecuniary poverty, particularly in low-income households. This aligns with the findings of Shimeles et al. (2018), which show that risk-taking farmers are more inclined to adopt new technologies, leading to higher income and subsequently reduced poverty.

The study also reveals reduced non-pecuniary poverty among the richest female-headed households and accentuated poverty among those who belong to the poorest categories. This is consistent to Doss (2018) who found that female farmers are mostly involved in subsistence agriculture and face various challenges including access to information and markets. Women in the poorest categories may end up accepting a low farm gate price because of other households' responsibilities, which increases transaction costs to distant markets. This, consequently, worsens their poverty status as they finally buy food staples at higher prices (net loss).

Generally, adopting non-mandatory cash crops would have reduced poverty among all income quantiles of smallholder farmers nevertheless this study resulted in contradicting findings because the adoption of non-mandatory cash crops was found to be not statistically significant. These findings corroborate those by Diao et al. (2010a) and Gong (2020) who assign credit to agriculture in poverty reduction, especially staple food, even though it may take quite some time Keswell and Carter (2014). Conversely, Habiyaremye (2017) confirmed that the adoption of non-mandatory cash crops like sericulture reduces poverty among farmers.

In Table 2 results on the effect of risk attitude alone on non-pecuniary poverty among smallholder farmers who participated in a quasi-experiment to establish their risk aversion, loss aversion and probability weighting parameters are presented. They show that the more smallholder farmers overweight high probabilities and underweight low probabilities, the more their non-pecuniary poverty declines especially in the two lowest quantiles of the multidimensional poverty index ($p = 0.000 \mid \beta = -0.052; p = 0.022 \mid \beta = -0.056$) for 0.10 and 0.25 quantiles respectively. Loss aversion and risk aversion characteristics of farmers do not significantly affect the non-pecuniary poverty status among smallholder farmers.

The results in Table 2 show that non-poor smallholder farmers that overweight high probabilities and underweight low probabilities were likely to further reduce their non-pecuniary poverty; the results may be justified by the fact that the above-mentioned households can make the correct decision in investing in appropriate crops while coping with the state of the nature like drought, floods, or other disasters outbreaks. Love et al. (2014) demonstrate the same by highlighting that probability weighting among smallholder farmers influences their agricultural investment whereby farmers who overweight low probability of a natural disaster occurrence stick to crops that are resilient to the disaster.

Table 2. Quantile analysis of effects of farmers' risk attitude on nonpecuniary poverty.

MPI	Coef.	St.Err.	t-Value	*p*-Value	[95% Conf	Interval]	Sig
q10							
sigma	−0.041	0.038	−1.08	0.282	−0.117	0.034	
alpha	−0.052	0.01	−4.96	0	−0.072	−0.031	***
lambda	−0.002	0.001	−1.63	0.105	−0.004	0	
Constant	0.14	0.018	7.85	0	0.104	0.175	***
q25							
sigma	−0.034	0.034	−1.00	0.318	−0.1	0.033	
alpha	−0.056	0.024	−2.33	0.022	−0.104	−0.008	**
lambda	−0.003	0.002	−1.48	0.142	−0.006	0.001	
Constant	0.174	0.033	5.33	0	0.109	0.239	***
q50							
sigma	−0.047	0.073	−0.64	0.52	−0.192	0.098	
alpha	−0.033	0.039	−0.85	0.398	−0.11	0.044	
lambda	0.003	0.005	0.50	0.616	−0.008	0.013	
Constant	0.175	0.052	3.34	0.001	0.071	0.279	***
q75							
sigma	0.133	0.146	0.91	0.364	−0.156	0.423	
alpha	−0.024	0.065	−0.38	0.707	−0.153	0.104	
lambda	0.005	0.007	0.78	0.438	−0.008	0.019	
Constant	0.232	0.056	4.14	0	0.121	0.343	***
q90							
sigma	0.115	0.089	1.29	0.2	−0.061	0.291	
alpha	0.021	0.057	0.36	0.719	−0.093	0.134	
lambda	0.003	0.005	0.53	0.6	−0.007	0.012	
Constant	0.282	0.059	4.77	0	0.165	0.399	***
Mean dependent var		0.185		SD dependent var			0.113

*** $p < 0.01$, ** $p < 0.05$.

It is crucial to notice that adopters were found to overweight small probabilities and underweight high probabilities. As price fluctuation and/or lack of market are likely to happen, it is probable that adopters underweight their occurrence probabilities and adopt non-mandatory cash crops. Consequently, adopters may find themselves deepening their non-pecuniary poverty level than non-adopters as shocks affect their income. Ashraf et al. (2008) concluded the same showing that products may be rejected by exporters who endeavour to comply with developed countries' niche markets required standards, hence after inducing adopters in poverty.

4. Conclusions

Non-income poverty was more accentuated among smallholder farmers who adopted non-mandatory cash crops, precisely in the richest categories of farmers that belong to the quantiles below the median quantile. Adopters who belong to the poorest categories, this is median and above quantiles were likely to reduce non-pecuniary poverty, although not significantly.

Factors like age, farm size, market accessibility, cooperative membership, education and sometimes being a risk taker significantly reduce the MPI among smallholder farmers, however, age exhibits a diminishing marginal utility in non-pecuniary poverty reduction. The diminishing marginal utility of age in MPI is supported by positive coefficients of age squared as a predictor. The more educated farmers the higher the potential to reduce non-pecuniary poverty. This is likely because they value and understand the importance of health insurance affiliation, benefits of good housing conditions and balanced diets.

Other factors like placing a high opportunity cost to the time spent on off-farm activities (especially among elderly and female-headed households), and the risk attitude of farmers like never taking risks, or mostly not taking risks were found significant in increased non-pecuniary poverty among smallholder farmers.

Finally, results show that the more smallholder farmers overweight high probabilities and underweight low probabilities, the more their non-pecuniary poverty was reduced particularly in the two lowest quantiles of multidimensional poverty index. This can be justified by engaging in agricultural activities after carefully assessing risks, particularly in terms of prices and market availability.

More efforts in the promotion of non-mandatory cash crop production could be made in the poorest category of households because the multidimensional poverty index is reduced if the poorest farmers grow non-mandatory cash crops more than non-adopters and the same category could benefit from any kind of training and formal education as it was proven to significantly contribute to the reduction of multidimensional poverty among poorest categories of smallholder farmers of adopters.

Policies aiming at improved welfare of elderly and female-headed households could consider enhanced opportunities for the mentioned groups to have access to off-farm activities in rural areas, information as well as access to niche markets.

Existing strategies like risk insurance that aim to hedge against risks associated with the new non-mandatory cash crop production could be emphasised and even scaled up and out to various sources of risks other than natural disasters. This is because farmers' willingness to adopt new technologies is related to their risk attitude, hence after, determining their poverty status.

Author Contributions: Conceptualization, P.U., G.A.O. and O.A.I.; methodology P.U., G.A.O. and O.A.I.; software, P.U.; validation, G.A.O. and O.A.I.; formal analysis, P.U.; investigation, P.U.; resources, P.U.; data curation, P.U.; writing—original draft preparation, P.U.; writing—review and editing, P.U., G.A.O. and O.A.I.; visualization, P.U.; supervision, G.A.O. and O.A.I.; project administration, P.U.; funding acquisition, P.U. All authors have read and agreed to the published version of the manuscript.

Funding: This research is part of a PhD research project and was funded by African Economic Research Consortium/DAAD 2017(57376089), under the personal reference number 91672905, grant number 2017(57376089).

Institutional Review Board Statement: The permission to conduct the research in Rwanda is issued in accordance with Ministerial Instructions 003/2010 of 09/12/2010 regulating research activities in Rwanda, NCST (National Council for Science and Technology) Ref: 151/NCST 2019.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the authors.

Acknowledgments: We are grateful to African Economic Research Consortium/DAAD for funding the PhD study whose one of the outcomes is a thesis with this specific article as one of the chapters. I do thank smallholder farmers, enumerators and local authorities for their contribution in easing data collection. Additionally, all authors are thankful to the manuscript reviewers for contributing to improving its quality.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Dimensions, indicators, cut-offs for deprivations and weights of MPI.

Dimensions	Indicators	Deprived If...	Weights
Education	Years of schooling	There is no member aged thirteen years or older who has completed six years	1/6
	Child school attendance	Any child at school-age is not attending school up to thirteen years	1/6
Health conditions	Health affiliation	Affiliated members of household/Total household members are less than 50%	1/6
	Child mortality	Any child died in the past five years	1/6
Housing conditions	Improved sanitations *	Household's sanitation improved but shared or not improved	1/18
	Flooring and walls	The type of floor is other cement or tiles, and the wall is in wood, shrubbery and plastic sheets	1/18
	Electricity	The house has no electricity	1/18
	Cooking fuel	The household does not use electricity or gas	1/18
	Clean drinking water **	Clean drinking water is at least thirty minutes' walk (round-trip)	1/18
	Assets ownership	The household does not own a radio, a TV, a bicycle, a car or truck	1/18

* A household is regarded as having access to improved sanitation in case it has not shared flush toilet or latrine, composting toilet or ventilated improved pit; ** A household has access to clean water if its source is of the following types: piped water, borehole or pump, public tap, protected well, protected rainwater or spring and that within a walk distance of thirty minutes (round trip) Source: Adapted from Alkire and Seth (2015).

Note

1 Rwanda's decentralized administrative layers consist of Provinces, Districts, Sectors, Cells and Villages. Cells are the lowest administrative unit that is responsible for community mobilization, data reporting and the provision of administrative documents to the citizens. Districts are the most important layer of the decentralization systems that are characterized by financial and legal independence

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