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Export horticulture and household welfare: Evidence from Zambia

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Evidence is very scanty in Africa on the welfare effects of the recent shift of the horticulture industry from involving poor households through outgrower arrangements towards employing them in consolidated production entities. This study determines the impact of large-scale export vegetable production on the welfare of the employees in Zambia. It uses data from a survey of a random sample of farm worker households and comparison households in nine villages around one of the four largest estate vegetable farms in Zambia. Evidence from control function, propensity score matching, and odds-weighted regression models suggest huge and significant welfare effects as measured by per capita consumption expenditure. Estimated at 44 and 45% for non-food and food expenditure, respectively, the impact is not affected by the households' initial wealth in any statistically significant manner. This means that the recent industry changes might need to be supported and better understood, as opposed to being admonished.

Key words: Zambia, labor, welfare, consumption, propensity score.

INTRODUCTION

With a per capita income of USD 423 and 64% of the Zambia's population (which is estimated at 12.5 million), living below the poverty line (World Bank, 2011), Zambia ranks among the poorest countries in the world. About 56% live in rural areas (World Bank, 2002) of which 97.4% are engaged in agriculture (CSO, 2000). Within a labor force of 3.4 million, 85% are employed in agriculture, 6% in industry and 9% in services. With unemployment at 7.9% (CSO, 2008), agriculture is often the only potential source of livelihood or income within the informal sector. The Zambian agricultural sector contributes about 20% to real GDP and 39% of earnings from non-traditional exports (IMF, 2011). The sector mainly consists of smallholder farmers who make up about 52% of the country's farmers (Chipokolo, 2006) and contribute 80% of the nation's food. However, despite their substantial aggregate contribution to national food supply and GDP, smallholder farmers constitute a third of the nation's hungry and poor (CSO, 2004). Several factors have been cited for the low welfare levels among smallholder farmers, including low productivity, frequent droughts, and unsatisfactory access to markets, market information and credit facilities (Chiwele, 2004; USAID, 2005). Export horticulture (flowers and vegetables) in Zambia developed in the early 1980s and growth in the sector in the last decade is seen as one of the opportunities for raising welfare levels among the rural poor, while also generating foreign exchange

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(Hichaambwa, 2010). In the 1990s and early 2000s, the industry expanded rapidly as numbers of companies increased, raising export volumes of vegetables and cut flowers from US $6 million in 1994 to over $33 million in 2001 when the sector employed about 10,000 people (ZEGA, 2002). However, most of these gains in both export volume and earnings were lost in 2005 (Hichaambwa, 2010).

The decline was due mainly to the demise in 2004 of the largest horticultural export company, Agriflora.[1] For smallholder farmers who participate in the industry under contract with larger firms, the bankruptcy of Agriflora deprived them of reliable income, transport logistics and technical support. Although, donors tried to cushion part of the shock, their support could not be sustained indefinitely. The industry also faces a number of other challenges, including exchange rate fluctuations (Sergeant and Sewadeh, 2006), inelastic prices in traditional markets (Mataa and Hichaambwa, 2010) and high air freight costs (ZEGA, 2002) that exceed levels observed in most other countries in the region.[2] Tightening standards in the UK and other EU export destinations in recent years have also served a major blow to the Zambian horticultural sector, especially among smallholder producers. It is argued that the cost of compliance to the European retailers' private standards for Good Agricultural Practices (EurepGAP) cut farmers' incomes in half between 2002 and 2006 (AgriFood Standards Project, 2007).

As a result, less than 3% of the smallholder farmers involved in supplying European markets in 2000 were still doing so in 2006. Most large-scale exporters have employed three major coping strategies. The first is to significantly reduce output and concentrate on the higher-value and higher-margin lines. The second strategy is to increase output and try to reduce costs, that is, improve efficiency to increase margins. The third strategy has been to reduce or eliminate all outgrower arrangements with smallholder farmers, increasingly placing greater emphasis on consolidation and "own" production.[3] However, the shift from smallholder contract-based farming to large-scale estate production may imply more employment for rural households (Dolan and Humphrey, 2000). A number of studies have considered the impact of export horticulture on household income and poverty in Africa. In Kenya, McCulloch and Ota (2002) found that households involved in export horticulture were better off, particularly in rural areas. They further contend that enabling more households to participate in the sector could reduce poverty substantially in both rural and urban areas.

Maertens and Swinnen (2009) used company and household survey data from the vegetable export chain in Senegal to quantify income and poverty effects of high standards trade through labor markets. They found that horticultural exports from Senegal to the EU had grown sharply despite strongly increasing food standards, and that these exports had strong positive effects on poor households' incomes, reducing regional poverty by about 12% and extreme poverty by half. Third, tightening food standards induced structural changes in the supply chain including a shift from smallholder contract-based farming to large-scale integrated estate production. These studies offer valuable lessons on the poverty-reducing effects of export horticulture. However, low-income countries are characterized by varying cost structures, levels of development and institutional sophistication, and experiences, all of which leave part of the debate for much of Africa still open.

The Zambian industry has faced relatively greater challenges adjusting to tightening standards due to a number of other unique structural constraints, including, as already outlined, the collapse of the largest market player, higher transport costs[4], and macroeconomic factors (high agricultural taxes and unstable exchange rates). This study uses data from 41 farm worker households and 64 comparison households to determine the impact of large-scale export vegetable production on the welfare of employees. It also seeks to determine whether the household's initial wealth has significant effects on the level of impact. Most of the prior studies cited earlier use income as a proxy of welfare. We use consumption expenditure as the outcome variable. As a proxy of welfare, consumption expenditure is often argued to be more reliable and less prone to under-reporting errors than income. We find huge and significant effects on consumption. At least, 49% of the farm workers' consumption can be attributed to participation in large scale estate horticultural farm activities. This is consistent with recent similar studies (Maertens and Swinnen, 2009; McCulloch and Ota, 2002) and challenges conventional arguments that consolidation of large-scale farms is bad to poor households.

METHODOLOGY

Impact identification strategy

Program impact can be defined as the expected value of the difference between the level of the outcome variable attained by participating households and that which they would have attained

[1] Agriflora got into financial difficulties in 2004, leading eventually to it going into administration. Some of its assets were sold to other exporters, but a significant amount of its production was lost and has not been recovered.

[2] The main cost of running a cargo aircraft is the cost of aviation fuel which is about 50% of the direct costs associated with cargo aircraft thus making the cost in Zambia much more expensive than other competing countries in the region, by 40 to 50% (ZEGA, 2002).

[3] Outgrower arrangements normally cover a range of services provided by the large companies, including pricing of inputs, input advances (charged with interest) and the price paid for produce supplied to the company.

[4] Because it is landlocked and located a long way from the lucrative EU markets, Zambia lacks easy access to ports. This renders Zambia incapable of competing effectively in the EU wholesale and other low-value markets (AgriFood Standards Project 2007).

had they not participated in the program (Wooldridge, 2002; Ravallion, 2001). That is:

$$ATT = E(Y_{1i} - Y_{0i} \mid w_i = 1) \cdot \quad (1)$$

Where *ATT* is the average treatment effect on the treated, Y_{1i} is per capita consumption expenditure (the outcome of interest) for the treatment group (that is, households supplying labor to the large horticultural farm), Y_{0i} is the outcome of interest for the comparison group, w_i is a dichotomous variable equal to one if the household has at least one of its members supplying labour to the large-scale horticultural farm and zero otherwise, and $E(.)$ is the expectations operator.

Consumption expenditure was computed by adding together the values of all goods and services consumed by the household (purchased or own-produced) during the 12-month period prior to the survey. This was divided by household size to obtain per capita consumption expenditure. When the i^{th} individual participates in wage estate employment, their level of consumption expenditure is Y_{1i} and if they do not their income is Y_{0i}. This is the conditional mean impact, conditional on participation, also known as the treatment effect or the average effect on the treated (Wooldridge, 2002). However, if there is a difference in the mean of the outcome variable between participants and non-participants in the absence of the program, a bias will arise and this bias is given by:

$$b = E(Y_{0i} \mid w_i = 1) - E(Y_{0i} \mid w_i = 0). \quad (2)$$

This bias could be corrected if $E(Y_{0i} \mid w_i = 1)$ were known. Unfortunately, the level of participants' consumption expenditure had they not participated cannot be observed. However, had the program been assigned randomly, the participants and non-participants could have the same expected income in the absence of the program. In this case, the expected income of non-participants will correctly reveal the counterfactual. For most programs, randomization is not possible due to ethical, cost and other pragmatic reasons. In the case of vegetable estate employment, treatment households either self-select themselves and/or are deliberately chosen on the basis of their individual characteristics. Under such a quasi-experimental design, statistical controls must be used to address the differences between the treatment and control groups (Barker, 2000). Under some form of exogeneity (Imbens, 2004), most quasi-experimental impact studies estimate the conditional average treatment effect on the treated as:

$$ATT = E(Y_{1i} - Y_{0i} \mid \mathbf{x}, w_i = 1) \quad (3)$$

Where x is a vector of covariates.

The assumption implied by (Equation 3) is that conditioning on carefully selected covariates renders the household's treatment status independent of potential outcomes, such that the unobserved $E(Y_{0i} \mid w_i = 1)$ can be represented by the observed $E(Y_{0i} \mid w_i = 0)$. This makes it possible to attribute any systematic differences in the outcome variables between treated and control units with the same values of the covariates to the program in question. A more dimensionally appealing but equivalent version of 'selection on observables' involves replacing x in (Equation 3) with the estimated conditional probability of participation, or propensity score, defined as $\hat{p}(\mathbf{x}) = E(w = 1 \mid \mathbf{x})$ (Rosenbaum and Rubin, 1983).

Data and data sources

This study uses data from a cross-sectional survey conducted in 2009 in nine villages around Borassus Estate, one of the three largest export horticulture producers, located about 25 km west of Lusaka, the capital of Zambia. A total sample of 41 treatment (that is, farm worker households) and 64 comparison households (that is, poor households located in the same neighbourhood as farm worker households but with no members working on the large vegetable farm) was drawn using stratified random sampling. Selection of farm worker households was based on a sampling frame developed out of a farm register, whereas the sampling frame for the comparison households was developed through comprehensive listing of non-worker households within the same neighbourhood. The simple random sampling applied to each stratum/frame ensured that, within the stratum, every listed household had an equal chance of being selected into the sample. Although, the households in the two strata looked similar on the basis of visible characteristics (save for participation status), we also used matching techniques to ensure comparability. The 41:64 (or roughly 2:3) sample allocation ratio between the treatment and comparison strata was deliberately done to provide more matching options for each treatment households. Among other things, the household questionnaire elicited information about participation in the horticultural industry, other livelihood activities, as well as standard demographic and human capital status. It also collected detailed information regarding food, nonfood and durable goods consumption expenditures, which was used in the computation of consumption-based measures of welfare.

The study benefited from secondary data and publications obtained from various organizations, including the Ministry of Agriculture and Cooperatives (MACO), the Central Statistical Office (CSO), the World Bank (WB), NZTT, and other relevant publications. Discussions with personnel from the Zambia Export Growers Association (ZEGA), the Natural Resources Development College (NRDC)/ZEGA Training Trust (NZTT), and management of the three major horticultural farms provided valuable information on the sub-sector.[5] The resultant expanded understanding of the sub-sector also helped in the interpretation of the quantitative results.

Empirical models

Estimation of the propensity scores

Program impacts are measured by assessing whether a program changes the mean value of an outcome variable among participants compared with what the outcome would have been had they not participated. The central evaluation problem then is that participants cannot be simultaneously observed in the alternative state of no participation (referred to as the counterfactual) (Shahidur et al., 2010). Evaluators typically simulate the counterfactual by comparing program participants with a control with similar characteristics. Construction of the counterfactual determines the evaluation design, which is broadly classified as experimental or quasi-experimental. A key feature of the experimental design is complete randomization, which ensures that households in treatment and control groups are, on average, similar and that any observed systematic differences in the outcome variables after the intervention are attributable to the intervention (Table 2). However, randomization is not always possible in observational studies such as ours. Ravallion (2001, 2003) characterizes the various methods used to estimate impact under quasi-experimental conditions. As a second-best alternative for these conditions, for example, comparison can be facilitated by statistically constructing comparable treatment and comparison strata. Propensity score matching (PSM) presents a unique set of techniques for

[5] In general, the discussions provided a picture of a once-prosperous sub-sector that was unfortunately on a decline at the time of the study.

reconstructing an experimental environment out of non-random, quasi-experimental conditions. We use variants of propensity-score-based methods to estimate the impact of employment in estate horticultural firms on household consumption, where the propensity scores (PS), or conditional probabilities of participation (given the observed characteristics), were estimated using a probit specification:

$$\text{Prob}\left(w=1\,|\,\mathbf{x}\right)=\Phi\left(\theta+\boldsymbol{\delta}'\mathbf{x}+\varepsilon\right) \quad (4)$$

Where Φ is a standard normal cumulative distribution function (CDF), ε is an error term, θ is the intercept to be estimated, $\boldsymbol{\delta}$ is a vector of slope parameters also to be estimated, and x is a vector of covariates. Equation 4 was estimated using maximum likelihood (ML) procedures in Stata (StataCorp, 2008).

In general, participation can be explained by the household's observable characteristics associated with access to resources (land, capital, and labor) and information, skills and ability (age, education), preferences (age, ethnicity, demographic structure), and geographic location (Maertens and Swinnen, 2009). To avoid endogeneity, we use initial (2005) values of variables such as asset endowment and livestock ownership. To ensure consistency of the PSM, only covariates that exhibited significant correlation with the participation variable and/or the outcome variable were included in x. Propensity-score-based models are only as good as the quality of the matching and are valid only under certain identifying assumptions. The balancing effects of the propensity scores were tested using a number of procedures including stratification, *t* tests for the differences in covariate means between the two groups (participants and non-participants) before and after the matching (Rosenbaum and Rubin 1985), effectiveness in reducing standardized bias, and ability to drive the overall probit relationship to insignificance as measured by a joint likelihood ratio (LR) test and pseudo R^2 (Caliendo and Kopeinig, 2008).[6]

Estimation of impact

We use three broad categories of models to estimate the impact of participation on the outcome variable – the control function approach, propensity score matching, and propensity score weighting. Heckman and Robb (1985) showed that selection bias can be controlled by including a vector of covariates as control functions:

$$\ln\left(y_i\right)=\gamma+\lambda w_i+\boldsymbol{\beta}'\mathbf{x}_i+\mu_i \quad (5)$$

Where y_i is the outcome variable (in our case per capita consumption expenditure) for household *i*, γ and λ are parameters to be estimated, β is a vector of parameters to be estimated, x is as defined above, and μ is a random error term.

Wooldridge (2002) contends that (equation 5) could be consistently estimated by OLS as long as the outcome variable is not correlated with the unobservable characteristics, also known as selection on observables. However, robust standard errors were used due to failure to reject heteroskedasticity. In the second specification of the control function approach, we replace x with the propensity score, a method pioneered by Rosenbaum and Rubin (1983):

$$\ln\left(y_i\right)=\gamma+\lambda w_i+\phi PS_i+\mu_i \quad (6)$$

Where the propensity score (*PS*) is as defined in (equation 1), that is, $PS_i=\hat{p}\left(w_i=1\,|\,\mathbf{x}\right)$, and ϕ is a parameter to be estimated.

In a more general version of correction on propensity score, we also include an interaction term between participation and the demeaned propensity score (Rosenbaum and Rubin, 1983; Wooldridge, 2002):

$$\ln\left(y_i\right)=\gamma+\lambda w_i+\phi PS_i+\varphi w_i\left(PS_i-\mu_{ps}\right)+\mu_i \quad (7)$$

Where μ_{PS} is the mean of the propensity score, and φ is a parameter to be estimated.

The results from the control function models (equation 5) through (equation 7) were corroborated with ones obtained through propensity score matching (PSM), which involves for each treatment unit finding matches in the control group based on observable characteristics (Abadie and Imbens, 2002; Dehejia and Wahba, 2002). Thus, the ATT was computed as the weighted average of the difference in the outcome variable between treatment households and matched control ones, where matching was done by kernel functions and ATT computation was restricted to the region of common support. The kernel matching estimator is given as (Heckman et al., 1997; Smith and Todd, 2005; Gilligan and Hoddinott, 2007):

$$ATT=\frac{1}{n}\sum_{i\in T}\left\{Y_{1i}-\frac{\sum_{j\in C}Y_{0j}K\left(\frac{P_j(\mathbf{x})-P_i(\mathbf{x})}{a_n}\right)}{\sum_{k\in C}K\left(\frac{P_k(\mathbf{x})-P_i(\mathbf{x})}{a_n}\right)}\right\} \quad (8)$$

Where *T* is the treatment group participants; *C* refers to the comparison group, *K* is the kernel function, and a_n is the kernel bandwidth. Inferences were made possible by bootstrapping standard errors.[7]

While matching produces consistent estimates, Hirano et al. (2003) show that the odds-weighted regression approach to PSM, or propensity score weighting (PSW), results in fully efficient estimates. Under this framework, impact is the estimated slope coefficient $\hat{\lambda}_1$ in the simple regression model:

$$y_i=\gamma+\lambda w_i+\mu_i \quad (9)$$

But with the observations weighted by 1 for treatment households and by the estimated odds ratio, $\hat{P}(\mathbf{x})/\left(1-\hat{P}(\mathbf{x})\right)$, for comparison households, where $\hat{P}(\mathbf{x})=E\left(w=1\,|\,\mathbf{x}\right)$ is the estimated conditional probability of participation.

Heterogeneous impact

The Hirano et al. (2003) framework can be extended to the case where the impact of the treatment is differentiated by some defined

[6] A well-balanced propensity score is necessary for artificially constructing an experimental environment from a quasi-experimental situation. The idea is that there should be no association between treatment status and each covariate once the observations have been restricted to the region of common support.

[7] Kernel matching, unlike nearest-neighbor matching, arguably leads to more valid bootstrapped standard errors (Abadie and Imbens, 2005; Gilligan and Hodinott, 2007).

household categorization. We use this framework to estimate disaggregated impact:

$$\ln(y_i) = \gamma + \lambda w_i + \pi w_i * D_i + \mu \quad (10)$$

Where D is a dummy variable based on the household's initial wealth status.

A household was categorized as poor (D = 1) if the initial wealth index was negative, where the wealth index was computed from assets data using principal components analysis (Filmer and Pritchett, 2001). Thus, the impact of participation is equal to $\hat{\lambda}$ for the relatively less poor households (D = 0) and $\hat{\lambda} + \hat{\pi}$ for the poor ones. Thus, $\hat{\pi}$ is the additional impact that a poor household would experience relative to its relatively richer counterparts.

RESULTS AND DISCUSSION

Table 1 presents selected sample characteristics, comparing control and treatment households. The results indicate that the two sub-samples were generally well-balanced with respect to most characteristics. Significant differences between control and treatment households were evident only with respect to the age of the household head, location and initial wealth of the households. Although, the age of the household head was generally low (averaging 40 years), households with at least one estate farm worker had generally younger heads compared to their non-worker counterparts. Treatment households were also more likely to be male-headed, to have more educated members, and to be further away from the main road and schools; although, these differences were not statistically significant. Not only did treatment households have greater initial wealth but they also were well-off as indicated by a positive mean wealth index. On the other hand, households in the control group were generally poor (windex < 0). At the time of the survey, treatment households also had almost twice as much consumptions as their counterparts in the control group, and this was true even if consumption was disaggregated into its components (Figure A2). These general descriptive results were further confirmed by probit analysis of participation (Table 2). The marginal effects (column 2) show that an additional year to the age of the household head was associated with a 1.3% drop in the household's probability to participate in estate wage employment. Surprisingly, the probability to participate was inversely and significantly correlated with the number of members in the active age group (15 to 55 years). Location and initial wealth were the largest determinants of participation.

The PS balancing test results confirm the existence of strong bias for most covariates and that balancing successfully eliminated this bias (Table A1).[8] In general, matching produces consistent estimates as long as the unobserved factors are equally distributed between the two groups.[9] The estimated PS was also inspected for the common support requirement. This was found to be satisfied, as indicated by the fact that 0 < PS < 1 and by a large PS overlap (0.07, 0.86) between the control and treatment groups (Figure A1).

Impact estimates

The descriptive statistics discussed earlier indicate that those who participate in estate horticulture firms as workers are better off as indicated by wealth and consumption. However, descriptive statistics are limited and may not imply causality as they fail to account for other sources of the observed differences. Table 3 presents impact estimates as determined by the various models discussed earlier. All the five models indicate huge positive and significant effects of participation. More specifically, employment in estate horticulture farms raises per capita household consumption by 49 to 53%. Although, the specific impact estimates vary from model to model, they are generally very close to each other. The control function models (columns 1 through 3) further confirm the importance of conditioning on the observables, either directly (column 1), or through the propensity score (columns 2 and 3). The interaction between the treatment indicator and the demeaned propensity score had a dampening but insignificant effect. Model 1 also shows that per capita consumption expenditure is directly correlated with education level attained by the members, and inversely related to household size. Village 2 households had 21% less consumption, just as they were less likely to participate compared to households in all other villages. Table 4 presents impact estimates disaggregated by initial wealth and category of consumed items based on the odds-weighted regression analysis (Hirano et al., 2003).

The results re-confirm the significance of consumption effects, ranging from 46% for relatively non-poor households, to 56% for poorer ones. The greatest difference between poor and non-poor households was with respect to food items; although, impact heterogeneity across wealth strata was generally not statistically significant.

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[8] In addition to covariate t tests, the estimated propensity score also satisfied the balancing property within an optimally determined number of strata or blocks (Becker and Ichino, 2002). Estimation of the propensity score and generation of balancing tests were achieved through a combination of psmatch2 (Leuven and Sianesi, 2003), pscore and pstest (Leuven and Sianesi, 2003) procedures in Stata.

[9] A key identifying assumption for the PSM is that there should be no unobserved factors that influence both participation and the outcome variable. This is variantly called in the literature as the conditional independence assumption (CIA), matching on observables, unconfoundedness, etc. 'Hidden bias' would be of concern if this assumption is violated (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008; Jalan and Ravallion, 2003; Cameron and Trivedi, 2005).

Table 1. Descriptive characteristics.

Variable	Variable description	Overall	Control units	Treated units
		(1)	(2)	(3)
n	Number of observations	105	64	41
Demographics			**Means**	
hage	Age of hh head (years)	40.48	42.05	38.03**
hsex	Male-headed households (%)	75.00	73.00	78.00
hedu	Education level of the head (years)	7.66	7.33	8.17
mxedu	Education of most educated member (years)	8.89	8.63	9.29
dmar	Households with married heads (%)	66.00	63.00	71.00
c 0 to14	Children 0 to 14 years old	2.06	2.02	2.12
m 15 to 55	Male members 15 to 55 years old	1.84	1.94	1.68
f1 5 to 55	Female members 15 to 55 years old	1.87	1.97	1.71
m 56plus	Elderly members 56 years or older	0.15	0.14	0.17
deprat	Dependency ratio (%)	38.27	37.06	40.16
nlab	Number of members providing labor	1.90	1.97	1.78
hhsize 05	Household size in 2005	5.27	5.39	5.07
Accessibility				
kmroad	Distance to nearest main road (km)	0.54	0.49	0.61
kmpsch	Distance to nearest primary school (km)	0.52	0.49	0.56
kmssch	Distance to nearest secondary school (km)	18.32	18.30	18.35
Location				
dvil2	Households in village 2 (%)	30.00	36.00	20.0*
dvil7	Households in village 7 (%)	27.00	28.00	24.00
dvil8	Households in village 8 (%)	31.00	33.00	29.00
dvilr	Households in other villages (%)	10.00	3.00	20.0**
Initial wealth				
windex	Asset wealth index in 2005	-1.62E-09	-0.23	0.36***
tlu 05	Tropical livestock units in 2005	0.25	0.20	0.31
area	Landholding size (ha)	0.52	0.49	0.58
Welfare				
texp	Consumption expenditure (million ZMK)	3.06	2.44	4.03***

Test of statistical significance of mean differences between treatment and control/comparison households: *** p<0.01, ** p<0.05, * p<0.1 . Dependency ration was computed as the ratio of inactive members to household size. Asset wealth index was computed with principal components analysis as in Filmer et al. (2001). Villages 1, 3 to 6, and 9 had very low frequencies. Thus, they were grouped together into dvilr. Source: Data from estate horticulture worker survey (2009).

Conclusions

Poverty is widespread in low-income countries like Zambia. Encouragement of land and labor intensive industries such as export horticulture is seen by many as one way to reduce poverty. This study determined the impact of large-scale export horticulture on the welfare of the employees. Data were from a survey of rural households around one of the four major large-scale export horticultural farms about 25 km west of Lusaka. The results, based on eight alternative econometric specifications, consistently point to the existence of huge and positive consumption effects. On average, as much as 44 to 56% of the workers' per capita consumption expenditure could be attributed to their participation in the export horticultural industry. The impact was found to be greater for households that were poor to start with and especially with respect to food consumption; although, statistically, such differences were not significant. As the industry is undergoing structural transformation from contract farming towards consolidation, these results suggest that export horticulture could still play an

Table 2. Propensity score estimation with the probit model.

Variable	Variable description	Parameter estimate	Marginal effects
		(1)	**(2)**
_cons	Intercept	1.959* (1.080)	
hage	Age of the household head (years)	-0.033* (0.020)	-0.013
hedu	Education of the household head (years)	-0.017 (0.072)	-0.006
mxedu	Education of most educated member (years)	-0.008 (0.078)	-0.003
m 15 to 55	Male members 15 to 55 years old	-0.321* (0.180)	-0.121
f1 5 to 55	Female members 15 to 55 years old	-0.322* (0.180)	-0.121
m 56plus	Elderly members 56 years or older	0.246 (0.390)	0.093
hhsize 05	Household size in 2005	0.062 (0.120)	0.023
Windex	Initial asset wealth index in 2005	0.495*** (0.180)	0.186
tlu 05	Initial tropical livestock units in 2005	0.084 (0.270)	0.031
Area	Landholding size	-0.057 (0.250)	-0.022
Kmroad	Distance to nearest main road (km)	0.406 (0.360)	0.153
dvil2	Village dummy, 1 = village 2	-0.677* (0.380)	-0.237
Dvilr	Village dummy, 1 = villages 1, 3 to 6, 9	0.823 (0.550)	0.319
Number of observations		105	
Likelihood ratio Chi-sq		30.63***	
Pseudo R2		0.218	
Predicted probability		0.367	
Actual probability		0.391	

Dependent variable: Whether the household supplied labor to the large-scale horticultural farms (= 1) or not (= 0). Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Source: Data from estate horticulture worker survey (2009).

Table 3. Impact estimates based on the control function, propensity score matching and odds-weighted models.

Variable	Variable description	Model 1	Model 2	Model 3	Model 4	Model 5
		X as control functions	***PS* as control functions**	***PS* and demeaned PS as control**	**Propensity score matching**	**Odds- weighted regression**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**
Constant		13.12*** (0.26)	12.81*** (0.080)	12.80*** (0.10)	-	13.02*** (0.052)
w	Treatment, 1 = Estate worker	0.491*** (0.068)	0.492*** (0.087)	0.494*** (0.089)	0.535*** (0.096)	0.512*** (0.084)
PS	Propensity score	-	0.416** (0.17)	0.455* (0.25)	-	-

Table 3. Contd.

*w** (*PS- u ps*)	*w* interacted with demeaned *PS*	-	-	-0.0663 (0.34)	-	-
hage	Age of hh head (years)	0.0010 (-0.004)	-	-	-	-
hedu	Education of hh head (years)	0.002 (0.016)	-	-	-	-
mxedu	Education, most educated (years)	0.068*** (0.014)	-	-	-	-
m 15 to 55	Male members 15 to 55 years old	-0.04 (0.040)	-	-	-	-
f1 5 to 55	Female members 15 to 55 years	-0.0226 (0.042)	-	-	-	-
m 56plus	Elderly members 56 years or older	0.0392 (0.086)	-	-	-	-
hhsize 05	Household size	-0.125*** (0.029)	-	-	-	-
windex	Asset wealth index	0.0378 (0.036)	-	-	-	-
tlu 05	Tropical livestock units	-0.019 (0.037)	-	-	-	-
Area	Landholding size (ha)	-0.013 (0.044)	-	-	-	-
mmroad	Distance to main road (km)	0.013 (0.058)	-	-	-	-
dvil2	Village 2 dummy	-0.207** (0.091)	-	-	-	-
dvilr	Villages 1, 3 to 6, 9 dummy	0.018 (0.11)	-	-	-	-
Goodness of fit F statistic		13.56***	26.25***	17.35***	-	36.88***
Observations		105	97	97	97	97
R-squared		0.69	0.37	0.37	-	0.31

Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.Dependent variable: Natural log of per capita consumption expenditure.Source: Data from estate horticulture worker survey (2008).

Table 4. Heterogeneous impact estimates based on odds-weighted regression analysis.

Variable	Variable description	Category of expenditure		
		Total	**Food**	**Non-food**
		(1)	**(2)**	**(3)**
Constant		13.02*** (0.052)	12.10*** (0.045)	12.49*** (0.068)
w	Treatment, 1 = estate worker	0.456*** (0.084)	0.452*** (0.11)	0.440*** (0.10)
*w*D*	*w* interacted with wealth dummy	0.104 (0.13)	0.240 (0.15)	0.0127 (0.15)
Goodness of fit F statistic		20.21***	23.22***	10.89***
Observations		97	97	97
R-squared		0.32	0.37	0.19

Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Natural log of per capita consumption expenditure.Source: Data from estate horticulture worker survey (2009).

important role towards poverty reduction. This is somewhat contrary to conventional, and largely anecdotal, arguments, that large-scale commercial farms are exploitative. It also calls for a re-orientation of public sector support and emphasis from enhancement of contract farming alone to a mix of strategies that also include ways to enhance large-scale export production. For example, domestic and export tax regimes that promote large-scale export horticulture could eventually translate into welfare gains for the poor households that live around those farms.

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REFERENCES

Abadie A, Imbens GW (2005). On the failure of the Bootstrap for matching estimators. Unpublished. University of California, Berkeley.

AgriFood Standards Project (2007). Impact of EurepGap on small-scale vegetable growers in Zambia. Fresh Perspect. p. 6.

Barker JL (2000). Evaluating the impact of development projects on poverty. Washington DC: The World Bank.

Becker SO, Ichino A (2002). Estimation of average treatment effects based on propensity scores. J. Stata 2:358-377.

Caliendo M, Kopeinig S (2008). Some practical guidance for the implementation of propensity score matching. J. Econ Surv. 22(1):31-72.

Cameron CA, Trivedi PK (2005). Microeconometrics: Methods and applications. Cambridge: Cambridge University Press.

Central Statistical Office - CSO (2008). Living conditions monitory survey for 2007-2008. Government of the Republic of Zambia, Lusaka, Zambia.

Central Statistical Office - CSO (2004). Living conditions monitory survey for 2003-2004. Government of the Republic of Zambia, Lusaka, Zambia.

Central Statistics Office - CSO (2000). Agricultural and pastoral production small and medium scale holdings 1997-98: Structural type and post harvest data. Government of the Republic of Zambia, Lusaka, Zambia.

Chipokolo C (2006). Smallholder agriculture: Ignored goldmine. PELUM Zambia, Policy Brief Number 1.

Chiwele DK (2004). Agriculture development and food security in sub-Saharan Africa: Building a case for more support: A case study of Zambia. RuralNet Associates Limited, Lusaka, Zambia.

Dehejia RH, Wahba S (2002). Propensity score matching methods for non-experimental causal studies. J. Rev. Econ. Stat. 84(1):151-161.

Dolan C, Humphrey J (2000). Governance and trade in Fresh Vegetables: The impact of UK supermarkets on the African horticulture industry. J. Dev. Stud. 37(2):147-176.

Filmer D, Pritchett LH (2001). Estimating wealth effects without expenditure data or tears: An application to educational enrollments of India. J. Demogr. 38(1):115-132.

Gilligan DO, Hoddinott J (2007). Is there persistence in the impact of emergency food aid? Evidence on consumption, food security, and assets in rural Ethiopia. Am. J. Agric. Econ. 89(2):225-242.

Heckman J, Robb R (1985). Alternative methods for evaluating the impact of interventions. In: Heckman J, Singer B (Eds), Longitudinal analysis of labor market data. New York: Wiley, pp. 156-245.

Heckman JJ, Ichimura H, Todd PE (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. J. Rev. Econ. Stud. 64:605-654.

Hichaambwa M (2010). Developments in the horticultural supply chains in Zambia. Paper prepared for the global horticultural initiative video conference on post harvest and transport technologies: Reducing losses and improving quality fruits and vegetables in Eastern and Southern Africa.

Hirano K, Imbens GW, Ridder G (2003). Efficient estimation of average treatment effects using the estimated propensity score. J. Econ. 71(4):1161-1189.

International Monetary Fund (IMF) (2011). World economic outlook databases. IMF, Washington DC, USA.

Jalan J, Ravallion M (2003). Estimating the benefit incidence of an antipoverty program by propensity score matching. J. Bus. Econ. Stat. 21(1):19-30.

Leuven E, Sianesi B (2003). PSMATCH2: Stata module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Available at: http://ideas.repec.org/c/boc/bocode/s432001.html.

Mataa M, Hichaambwa M (2010). Smallholder involvement in commercial agriculture/horticulture in Zambia. Paper prepared for the video conference on high value agriculture in Eastern and Southern Africa.

Maertens M, Swinnen JFM (2009). Trade, standards and poverty: evidence from Senegal. World Dev. J. 37(1):161-178.

McCulloch N, Ota M (2002). Export horticulture and poverty in Kenya. Institute of Development Studies, University of Sussex, Brighton, UK.

Ravallion M (2001). The mystery of the vanishing benefits: An introduction to impact evaluation. WB Econ. Rev. 15(1):115-140.

Ravallion M (2003). Assessing the poverty impact of an assigned program. In Bourguignon F, Pereira da Silva LA (Eds), The Impact of economic policies on poverty and income distribution. Oxford University Press.

Rosenbaum P, Rubin D (1983). The central role of the propensity score in observational studies for causal effects. Biomed. J. 70:41-55.

Rosenbaum P, Rubin D (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. Am. Stat. 39:33-38.

Shahidur R, Gayatri B, Hussain A (2010). Handbook on impact evaluation: Quantitative methods and practices. The World Bank, Washington DC.

Sergeant A, Sewadeh M (2006). Current status of Zambia's agricultural exports. Paper prepared for the World Bank. Washington DC.

Smith JA, Todd PE (2005). Does matching overcome Lalonde's critique of non-experimental estimators. J. Econom. 125:305-353.

StataCorp (2008). Stata Statistical Software: Release 10. College Station, TX: StataCorp LP.

United States Agency for International Development (USAID) (2005). Economic growth: Increased private sector competitiveness in agriculture and natural resources. USAID/Zambia, Lusaka, Zambia.

Wooldridge JM (2002). Econometric analysis of cross section and panel data. The MIT Press: Cambridge, Massachusetts.

World Bank (2002). World Development Indicators. World Bank, Global Poverty Working Group. Washington DC.

World Bank (2011). African development indicators 2011. World Bank, Washington DC.

ZEGA (Zambia Export Growers Association) (2002). Publicity Brochure. ZEGA, Lusaka, Zambia.

Table A1. Balancing properties of covariates in treated and control groups.

Variable	Sample	Mean treated units	Mean control units	% Bias between treated and controls	% Reduction in |bias|	H_0: Mean (treated) = mean (control)	
						t	Probability > |*t*|
		(1)	(2)	(3)	(4)	(5)	(6)
hage	Unmatched	38.030	42.053	-43.3		-2.17	0.032
	Matched	38.971	37.688	13.8	68.1	0.58	0.561
hedu	Unmatched	8.171	7.328	29.8		1.53	0.128
	Matched	7.743	7.796	-1.9	93.7	-0.08	0.935
mxedu	Unmatched	9.293	8.625	26.0		1.34	0.182
	Matched	8.914	8.750	6.4	75.4	0.28	0.779
m 15 to 55	Unmatched	1.683	1.938	-21.3		-1.07	0.285
	Matched	1.571	1.654	-6.9	67.4	-0.36	0.723
f1 5 to 55	Unmatched	1.707	1.969	-23.5		-1.17	0.245
	Matched	1.714	1.652	5.6	76.0	0.24	0.809
m 56plus	Unmatched	0.171	0.141	6.3		0.33	0.743
	Matched	0.143	0.145	-0.5	92.8	-0.02	0.984
hhsize 05	Unmatched	5.073	5.391	-14.9		-0.78	0.437
	Matched	5.086	5.115	-1.4	90.7	-0.06	0.950
windex	Unmatched	0.364	-0.233	58.6		3.11	0.002
	Matched	0.100	-0.012	11.0	81.1	0.51	0.610
tlu05	Unmatched	0.312	0.204	13.5		0.74	0.463
	Matched	0.138	0.126	1.5	89.0	0.15	0.878
Area	Unmatched	0.578	0.490	12.4		0.61	0.540
	Matched	0.437	0.408	4.2	66.0	0.24	0.811
kmroad	Unmatched	0.607	0.494	24.4		1.26	0.210
	Matched	0.591	0.550	8.9	63.4	0.35	0.724
dvil2	Unmatched	0.195	0.359	-37.0		-1.81	0.073
	Matched	0.229	0.165	14.2	61.5	0.66	0.513
dvilr	Unmatched	0.195	0.031	52.9		2.87	0.005
	Matched	0.114	0.059	17.9	66.2	0.82	0.417

Note: Matching reduced pseudo R^2 from 0.218 to 0.032 and the overall likelihood ratio Chi-square for the probit relationship from 30.63 (p-value = 0.004) to 3.09 (p-value=0.998).

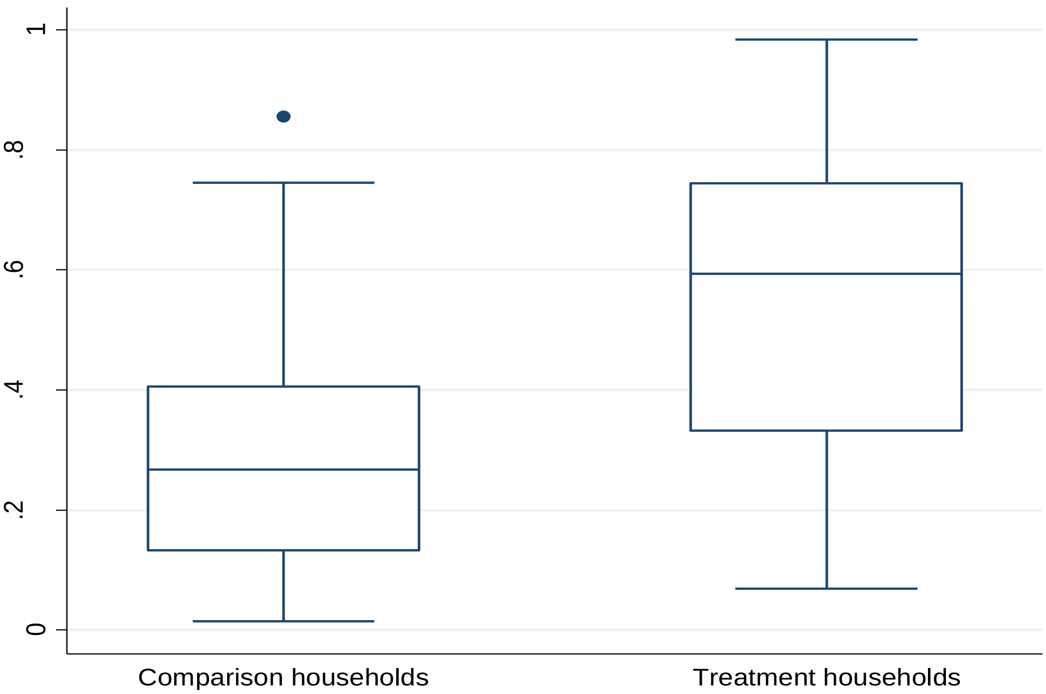

Figure A1. Distribution of propensity scores over comparison and treatment households. Notes: Common support requirement was satisfied within (0.070, 0.855).

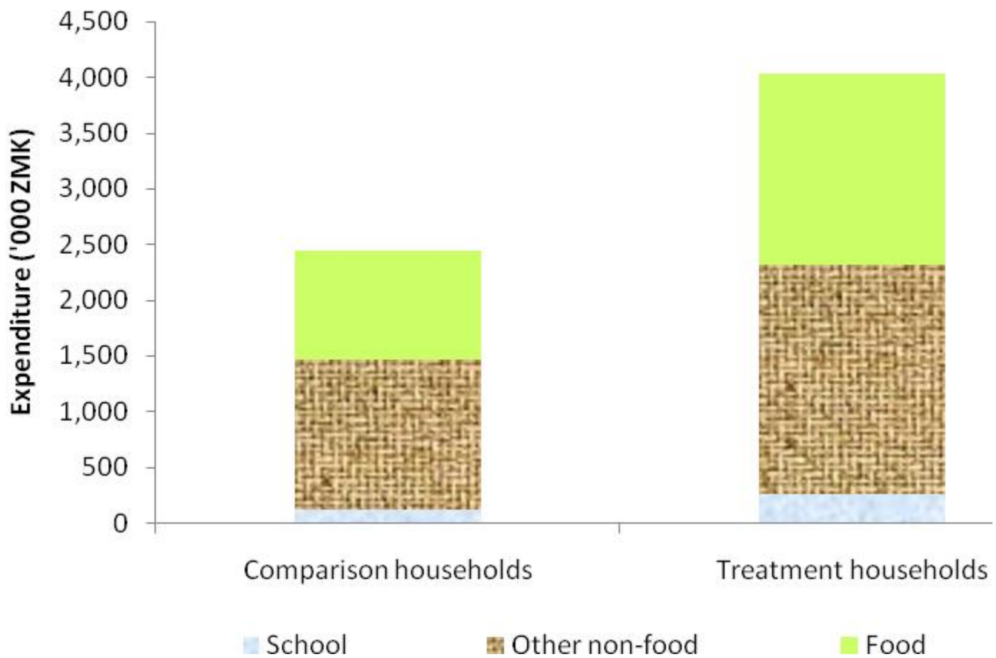

Figure A2. Expenditure patterns for comparison and treatment households.