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To Specialize or Diversify: Agricultural Diversity and Poverty Dynamics in Ethiopia

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Summary. — Recent agricultural development policies have begun to shift focus from the promotion of a few staple crops toward encouraging crop diversity. The belief is that crop diversification is an effective strategy for dealing with a variety of issues, including poverty alleviation. However, there is a lack of empirical evidence to justify these positions. We contribute to filling this research gap by providing quantitative evidence on the impact of diversity in crop cultivation on household poverty. Using household panel data from Ethiopia we develop a diversity index to measure the effect of crop diversity on poverty status. To control for endogeneity and selection bias resulting from unobserved heterogeneity we utilize a recently developed parametric method for estimating dynamic binary response models with endogenous contemporaneous regressors. Our results provide evidence that households which grow a diverse set of crops are less likely to be poor than households that specialize in their crop production. Additionally, crop diversity reduces the probability that a non-poor household will fall into poverty and the probability that a poor household will remain in poverty. We conclude that crop diversification is a viable way to deal with the exigencies of being poor.

Key words — crop diversity, poverty, control function approach, dynamic binary response models, rural Ethiopia

1. INTRODUCTION

Ex post, specialization in production will always be profit maximizing. However, the *ex ante* choice to specialize or diversify crop production is non-trivial. This is because there are numerous constraints and uncertainties in the agricultural production process that may result in households choosing to cultivate a diverse crop portfolio (Hardaker, Huirne, & Anderson, 1997). In recognition of this, an increasingly common policy prescription for smallholders has been agricultural diversification. Food and Agriculture Organization (FAO) policy supports crop diversification with the understanding that it may be an effective strategy for dealing with issues as varied as food and nutrition security, employment generation, sustainable agricultural development, environmental and ecological management, and poverty alleviation (FAO, 2012). A series of country-level case studies undertaken by the FAO recommend methods to increase crop diversity but provide no quantitative evidence to support the efficacy of these policies (Hazra, 2001; Kaguongo *et al.*, 2013; Mengxiao, 2001). Similarly, recent International Food Policy Research Institute (IFPRI) publications have argued that growth in agricultural incomes will require diversification by farming households (Taffesse, Dorosh, & Asrat, 2011). Despite this shift of focus by development agencies from the promotion of a few staple grain crops to policies designed to encourage diversification, there is a lack of rigorous empirical evidence to support these positions. We fill this research gap by providing some of the first clear, rigorous quantitative evidence on these policies. [1]

In the spirit of recent literature designed to assess the impact of specific development programs (Bezu, Kassie, Shiferaw, & Ricker-Gilbert, 2014; Jodlowski, Winter-Nelson, Baylis, & Goldsmith, 2016; Larsen & Lilleør, 2014; Loschmann, Parsons, & Siegal, 2015; Mendola & Simtowe, 2015), we formulate our research question as a test of the impact of diversity in crop cultivation on household poverty in Ethiopia. While there is no defined policy or program in Ethiopia to encourage diversification, there is a secular trend in our data of increased crop diversity among households. We develop a diversity index that measures the variety of crops under cultivation by a household in a given year. [2] We use this index to measure the effect of crop diversity on poverty status, controlling for endogenous regressors and selection bias resulting from unobserved heterogeneity. We use poverty as our outcome of interest because it provides insight regarding the distributional effects of crop diversity, that is, whether diversification can pull poor households out of poverty. Furthermore, the Millennium Development Goals make poverty reduction the central objective of development. Consistent with this, we follow Christiaensen, Demery, & Kuhl (2011) in focusing our analysis on poverty reduction and not household income or consumption growth. In addition to our primary research question, we formulate a second research question: what is the impact of crop diversity on the probability that a poor household will rise out of poverty or that a non-poor household will fall into poverty?

Assessing the impact of crop diversity on poverty is not straightforward, especially in the case where no specific program or no distinct treatment exists. Estimation is complicated by state dependence in the binary outcome in addition to two potential sources of endogeneity. First, it is likely that there are unobserved household characteristics (e.g., skill,

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entrepreneurship) that create selection bias in the choice to diversify. Second, the decision to diversify or specialize may be driven by negative shocks that also increase the probability of a household being poor. Instead of adopting the standard methods to assess causal impact, we utilize a recently developed approach to estimating dynamic binary response models with endogenous regressors (Giles & Murtazashvili, 2013). This new method allows us to account for the endogeneity in cropping decisions by employing a control function approach similar to Papke and Wooldridge (2008) while also accounting for the initial conditions problem and the existence of unobserved heterogeneity via a correlated random effects model developed by Wooldridge (2005).

We find that crop diversity has a positive and significant impact on reducing the probability of a household being in poverty. Specifically, a 10% increase in crop diversity reduces the probability of being poor by 18%. Furthermore, a 10% increase in crop diversity reduces the probability that a poor household will remain in poverty by 18%. Finally, a 10% increase in crop diversity reduces the probability that a non-poor household will fall below the poverty line by 17%. We conclude that agricultural diversification, not specialization, is associated with poverty reduction. Households which cultivate a variety of crops are less likely to be poor. Our results provide much needed evidence regarding the increasingly common policy prescription of agricultural diversification.

2. LITERATURE REVIEW

Much of the literature on smallholder cropping decisions is framed as a debate over whether it is better to specialize or diversify. Cash crops are often promoted to alleviate poverty through welfare gains as part of a strategy based on comparative advantage (Govereh & Jayne, 2003) while a diverse crop portfolio is promoted as part of a strategy to manage production risk (Rosenzweig, 1988). Specializing in cash crops, which are assumed to have a higher value than food crops, may directly increase a household's income. The production and sale of cash crops allows the household to earn, and thus consume, more than could be done by allocating the same resources to own-food production. [3]

However, the benefits of specializing in cash crops may be limited by agro-climatic conditions (Orr, 2000). [4] While predicted declines in poverty due to cash cropping are based on the Ricardian theory of comparative advantage, portfolio theory predicts that risk averse households will reduce production risk through crop diversification (Rosenzweig, 1988). Optimal crop mix will depend on the relative magnitudes of the variance and covariance of the crops in question. In Appendix A we develop a theoretical model of multi-crop production by risk averse agents to more formally demonstrate the mechanism by which crop diversity impacts poverty.

Within the literature on crop diversity, production risk, and income, the focus is generally on estimating the determinants of diversity. [5] Several studies find a positive relationship between household income and agricultural diversity (Barrett *et al.*, 2001; Caviglia-Harris & Sills, 2005; Ellis, 1998, 2000). Contrary evidence exists, however, indicating that greater diversity may be associated with poverty. Feder, Just, and Zilberman (1985) argue that income drives diversification, generating income gains for the already wealthy and resulting in a poverty trap for those at the bottom.

Instead of estimating the determinants of diversity we analyze the role diversity plays as a determinant of poverty. Fewer studies have taken this approach. Among studies that do, most treat diversity as an exogenous variable (Baird & Gray, 2014; Bezu, Barrett, & Holden, 2012; Bigsten & Tengstam, 2011). By failing to control for endogeneity in the choice to diversify, or control for the initial condition of households, these studies provide only suggestive results about the relationship between diversity and poverty. Our econometric methodology, which includes instrumenting for crop diversity, resolves these issues and provides clear evidence that diversity reduces poverty.

In addition to our contribution to the literature on the relationship between crop diversity and income, our work also contributes to recent research on household coping strategies to increase food security and adapt to climate change. Despite evidence that farms are becoming less diversified (Bradshaw, Dolan, & Smith, 2004), diversification has come to be viewed as an important way to increase food security. This is particularly true when faced with increasing variability in production due to climate change. Several studies conducted in Ethiopia find that combinations of different farming techniques, including greater crop diversity, may mitigate food insecurity and help farmers cope with climate change (Bezabih & Sarr, 2012; Di Falco, Veronesi, & Yesuf, 2011; Di Falco & Veronesi, 2013). Our results provide further evidence that crop diversification is a viable way to deal with the exigencies of being poor.

3. DATA

Our empirical analysis uses panel survey data collected in the Ethiopian Rural Household Survey (ERHS) by the Economics Department at Addis Ababa University, the Centre for the Study of African Economics at Oxford University, and IFPRI. The data cover approximately 1,500 households in 15 villages from 1989 to 2009. The villages were selected to provide coverage of the variety of farming systems in the country and thus are considered nationally representative of rural, non-pastoral households. We use a balanced panel of 1,015 households from six rounds of the survey covering 1994 to 2009. [6] For more details on the ERHS, see Dercon and Hoddinott (2011).

(a) *Poverty status and household characteristics*

Our dependent variable is a binary indicator that measures if the household was below the poverty threshold. Our decision to use a binary indicator is motivated by three factors. First, the primary concern of many development agencies is raising households out of poverty. By focusing on poverty status, our results are easily interpreted and speak directly to the mandate of many development stakeholders. Second, income and expenditure data in the ERHS are incomplete. [7] Due to heterogeneity in age and quality of durable and non-durable goods (as well as an inability to establish market prices for these goods), consumption data in the ERHS are limited to only food items and non-investment non-food items (Dercon *et al.*, 2009). By using a binary indicator for poverty we are able to minimize measurement error in calculating our dependent variable. Third, while use of a continuous dependent variable might provide more *precision* in coefficient estimates, our use of a binary dependent variable does not require any sacrifice in the *accuracy* of coefficient estimates. Thus, our use of a binary poverty indicator instead of a continuous consumption variable allows us to reduce measurement error in our dependent variable, makes our results easily interpretable, and does so at no cost to the accuracy of our estimates.

To construct our poverty indicator we follow Dercon *et al.* (2009) in using a cost-of-basic-needs approach that includes both food and non-food items. Food poverty is considered to be consumption of a bundle of food items that provide less than 2,300 kcal per adult per day. To this is added a bundle of non-food items as in Ravallion and Bidani (1994).[8] In our sample, 44% of households are below the poverty threshold. Relevant literature on the topic finds about 40% of rural Ethiopian households live below the poverty line (Bigsten, Kebede, Shimeles, & Taddesse, 2002; Bogale, Hagedorn, & Korf, 2005). This suggests that our poverty term is broadly representative. The share of households living in poverty in each village is highly variable. Gara Godo has the largest share of poor households, with 74% of households living below the poverty line. Sirbana Godeti has the smallest share of poor households, with only 13% of households living below the poverty line (see Table 1).

In this study we are particularly interested in the dynamics of poverty, in particular, how poverty responds to changes in crop diversity (see Table 2). However, given our binary poverty indicator and with only six observations per household, informative measures of household poverty dynamics are difficult to construct. To that end, our descriptive analysis focuses on poverty dynamics at the village level. Figure 1 displays the bivariate kernel density contours of the mean poverty level in each village in each survey year compared with the previous survey year. To this we have added a 45° line. Villages that, from one survey year to the next, have experienced an increase in household poverty are below the 45° line. By examining the density above the 45° line and comparing it to the density below the 45° line we can gain a visual picture of how poverty has changed over time. Encouragingly, much of the mass of the poverty distribution lies above the 45° line, indicating that most villages saw a reduction in poverty over the survey period.

This reduction in village-level poverty appears, at first glance, to be correlated with changes in crop diversity. Figure 2 is a scatter plot of changes to village poverty and changes to average village crop diversity from one survey year to the next. To this we add a linear trend line whose slope is positive and significantly different from zero. Taken together, Figures 1 and 2 provide suggestive evidence that, on average, households in Ethiopia are becoming less poor and that this dynamic is correlated with households becoming more specialized, not more diversified, in crop production.[9]

Table 2. *Descriptive statistics by year*

Year	Households	Poverty share		Crop diversity	
		Mean	St. Dev	Mean	St. Dev
1994	1,015	0.48	0.50	0.079	0.069
1995	1,015	0.56	0.50	0.135	0.127
1997	1,015	0.34	0.48	0.131	0.107
1999	1,015	0.37	0.48	0.196	0.200
2004	1,015	0.36	0.48	0.136	0.125
2009	1,015	0.52	0.50	0.132	0.124
Total		0.44	0.50	0.135	0.136

Note. Mean poverty share is the percentage of households in a given year that are below the poverty line. Mean crop diversity is the mean of the diversity index in each year.

In addition to our household poverty indicator, we also use a selection of household demographic characteristics to evaluate and control for the relationship between crop diversity and poverty status. These include household size, land per capita, and the years of education obtained by the head of household. We also include an indicator variable for whether or not the head of household is female. Descriptive statistics for these variables, as well as for poverty status, can be found in Table 3.

(b) *Crop diversity index*

To measure crop diversity we generate a crop diversity index, using detailed cropping data from the survey. Our index measures the total number of different crops a household grows in a year (n_{it}), relative to the total number of different crops grown within the village in that year (N_{jt}). We then square this ratio:

$$div_{it} = \left(\frac{n_{it}}{N_{jt}}\right)^2. \tag{1}$$

Table 1. *Village-level descriptive statistics*

	Households	Obs.	Poverty share		Crop diversity			
			Mean	St. Dev	Mean	St. Dev	Max	Total
Haresaw	63	378	0.52	0.50	0.085	0.106	6	16
Geblen	56	336	0.63	0.48	0.076	0.094	5	13
Dinki	56	336	0.62	0.49	0.072	0.073	8	20
Debra Birhan	125	750	0.20	0.40	0.228	0.158	10	24
Yetmen	41	246	0.33	0.47	0.265	0.244	9	19
Shumsha	79	474	0.22	0.41	0.064	0.064	10	27
Sirbana Godeti	63	378	0.13	0.33	0.186	0.171	9	19
Adele Keke	75	450	0.26	0.44	0.095	0.074	8	20
Korodegaga	77	462	0.52	0.50	0.175	0.113	8	13
Trirufe Ketchema	75	450	0.39	0.49	0.090	0.069	14	29
Imdibir	57	342	0.69	0.46	0.215	0.157	12	22
Aze Deboa	65	390	0.60	0.49	0.094	0.060	11	25
Adado	67	402	0.58	0.49	0.080	0.069	9	20
Gara Godo	71	426	0.74	0.44	0.166	0.122	12	22
Doma	45	270	0.43	0.50	0.091	0.091	7	22
Total	1,015	6,090	0.44	0.50	0.135	0.136		

Note. Mean poverty share is the percentage of households in each village that are poor averaged across years. Mean crop diversity is the mean of the diversity index in each village averaged across years. Max is the observed maximum number of crops grown by a household in each village while total is the total number of different crops grown in the village.

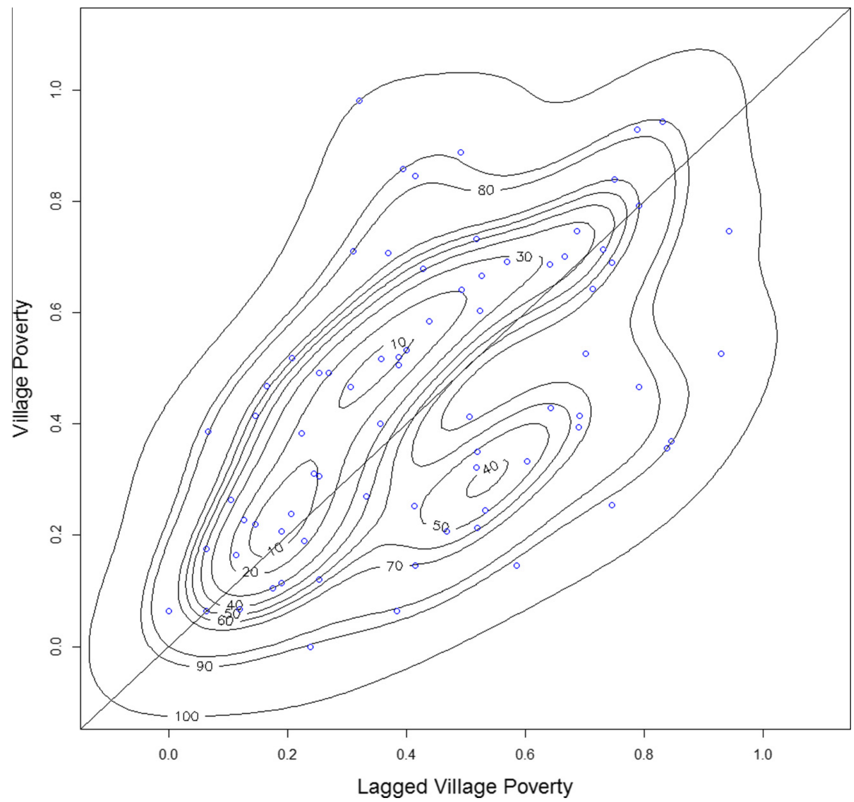

Figure 1. *Bivariate density of mean village poverty. Figure shows the bivariate kernel density contours of the mean poverty level in each village in each year. Poverty level is one hundred minus the percentage of households in the village that are poor. Thus, observations close to zero come from villages with high poverty levels while observations close to one come from villages with low poverty levels. Circles indicate observed data. Villages above the 45° line have fewer poor households compared to the previous year. Villages below the 45° line have more poor households compared to the previous year.*

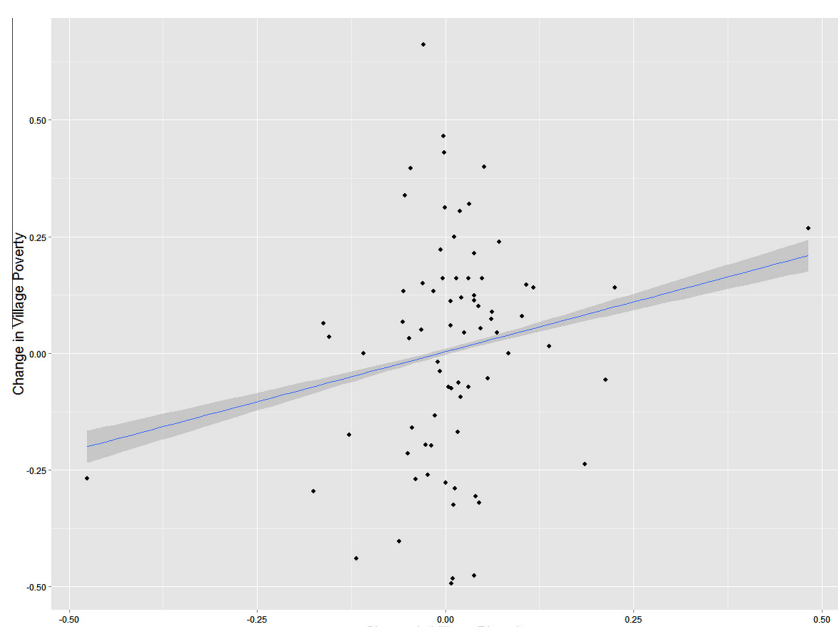

Figure 2. *Change in village poverty versus change in crop diversity index. Figure shows scatter plot of changes to village poverty and changes to village crop diversity from year t-1 to t. The figure also includes a linear trend line, with 95% confidence interval, with slope of 0.427, which is statistically different from zero at the 99% level.*

Table 3. *Household and village characteristics*

	Mean	St. Dev.
Poverty status (%)	0.44	0.50
Crop diversity index	0.14	0.14
Household size	6.13	2.76
Land per capita (ha)	0.28	0.33
Education (years)	1.38	2.51
Female headed household (%)	0.24	0.40
Distance to Ag coop (km)	6.02	6.06
Households	1,015	
Observations	6,090	

Note. Mean poverty share is the percentage of households in each village that are poor averaged across years. Mean crop diversity is the mean of the diversity index in each village averaged across years. Distance is a village-level variable measured from the center of the village to the nearest agricultural cooperative. For villages with a coop within village boundaries the distance is recorded as 0.01.

This approach has several advantages to alternative methods of index construction. [10] First, by using the total number of crops presently grown in the village as the denominator in our index, we can control for village-specific agro-climatic conditions. Thus, a household's crop diversity, or lack thereof, is not measured against the agricultural practices of households in other villages, but against the practices common to its own village. Households living in agronomic zones that allow for a limited number of crops are not penalized for only growing a few crops. [11] Second, we update the denominator of each survey year to allow for changes to the environment that might increase or decrease the number of different crops grown in a village. This allows us to accommodate the insight that in each village in each year a different cropping strategy might be welfare maximizing. Third, by measuring a household's diversity in relation to the total number of crops grown in the village, we can capture the inequality between households in a given community. In a recent paper, Thiede (2014) shows that adverse environmental events have heterogeneous effects on households within a village, disproportionately harming poorer households. By constructing our index in relation to village practices, we can explore the interaction between poverty status and crop diversity within the village.

As our index is a ratio, lower values indicate a more agriculturally specialized household relative to the cropping practices in the village and higher values indicate a more diversified household relative to the village. We include in our diversity count 50 different crops, including staple crops such as teff, maize, and barely, high-value crops such as vegetables, and cash crops such as linseed and sesame. Several types of tree crops are also included such as coffee, chat, enset, and various fruits. [12] Table 1 shows summary statistics of crop diversity for each village as well as the maximum number of crops grown by a household in the village and the total number of different crops grown in the village.

Similar to our examination of poverty dynamics at the village level, Figure 3 displays the bivariate kernel density contours of the mean level of diversity in each village in each survey year compared with the previous survey year. Villages that, from one survey year to the next, have experienced a decrease in crop diversity are below the 45° line. Much of

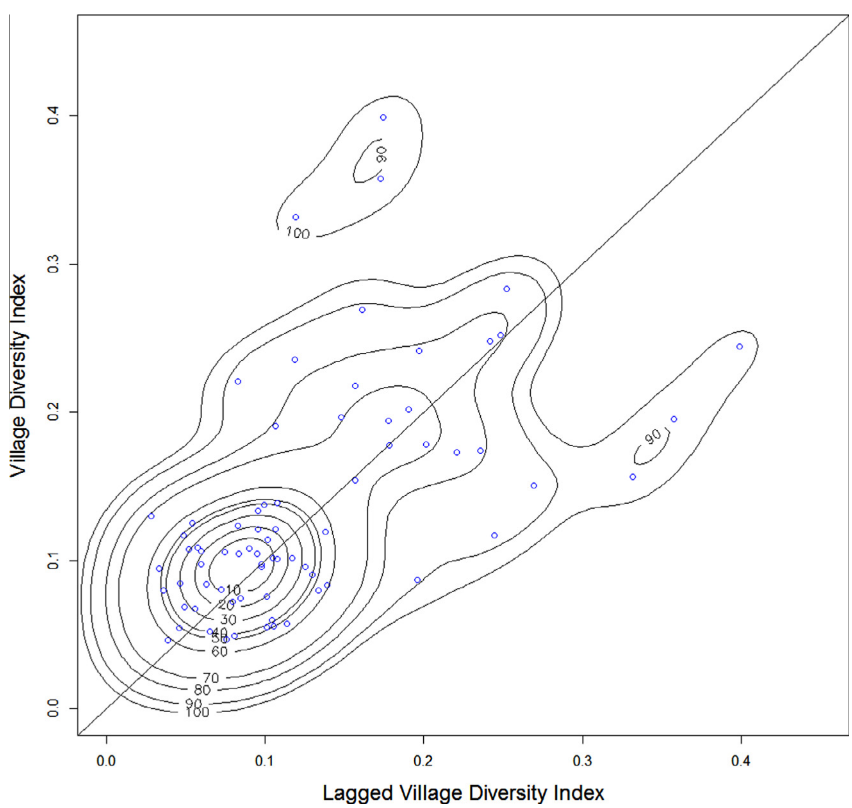

Figure 3. *Bivariate density of mean village diversity index. Figure shows the bivariate kernel density contours of the mean diversity index in each village in each year. Observations close to zero come from villages with low levels of crop diversity while observations close to one come from villages with high levels of crop diversity. Circles indicate observed data. Villages above the 45° line have more crop diversity compared to the previous year. Villages below the 45° line have less crop diversity compared to the previous year.*

the mass lies above the 45° line, indicating that most villages saw an increase in crop diversity over the survey period. Despite the increase in crop diversity and decrease in poverty over the survey period, as we saw in Figure 2, the correlation between these events appears to be negative. This result could be due to several reasons. One is that while, on average, poverty fell and diversity increased, the villages (and households within villages) that reduced poverty were not the same as those that increased crop diversity. A second reason is that our analysis is bivariate and fails to control for confounding factors such as endogeneity of the diversity index and the initial conditions problem. Our empirical strategy addresses these issues.

4. EMPIRICAL STRATEGY

Estimation of the relationship between crop diversity and poverty status faces numerous econometric issues. These include two potential sources of endogeneity. The first is the potential for unobserved heterogeneity, including state dependence, in our dynamic setting. The second is a simultaneity problem in that poverty and crop diversity may be co-determined. In this section we discuss these issues and briefly outline our method for dealing with them.

(a) *A dynamic binary response panel data model*

The first potential source of endogeneity is the existence of unobserved household characteristics or unobserved shocks affecting both cropping decisions and poverty status. In a dynamic panel data model, how unobserved characteristics affect the initial condition is an important problem to address. We use a control function approach introduced by Smith and Blundell (1986) and applied to a nonlinear setting by Papke and Wooldridge (2008).

We begin by assuming that for our binary response function, there is an underlying latent variable model:

$$y_{it}^* = \mathbf{z}_{1it}\beta_1 + \beta_2 x_{it} + \rho y_{i,t-1} + c_{1i} + u_{1it} \tag{2}$$

where $y_{it} = 1[y_{it}^* \geqslant 0]$ for $t = 1, \ldots, T$, $\mathbf{z}_{1it}$ is a $1 \times (K-1)$ vector of exogenous variables, x_{it} is an endogenous covariate, c_{1i} is an unobserved effect, u_{1it} is an idiosyncratic error term, and β_1, β_2, and ρ are parameters to be estimated.

Correct estimation of the model requires several assumptions. First, we assume that the dynamics in the model are correctly specified and $\mathbf{z}_{1it}$ is strictly exogenous conditional on the unobserved effect, c_{1i}. This assumption implies that the error term is serially uncorrelated. [13] Second, we assume that we can model the endogenous covariate as a linear function of the following variables:

$$x_{it} = \mathbf{z}_{1it}\delta_1 + \mathbf{z}_{2it}\delta_2 + c_{2i} + u_{2it} \tag{3}$$

where $\mathbf{z}_{2it}$ is a set of instrumental variables and u_{2it} is an idiosyncratic error term also free of serial correlation. Third, consistent with Mundlak (1978), we assume that the unobserved effect in the first-stage equation, c_{2i}, can be replaced with its projection onto the time averages of all exogenous variables such that

$$c_{2i} = \bar{\mathbf{z}}_i\lambda + a_{2i} \tag{4}$$

where $\bar{\mathbf{z}}_i$ is a vector of time averages of $\mathbf{z}_i = (\mathbf{z}_{1it}, \mathbf{z}_{2it})$. Following Papke and Wooldridge (2008), we can use Eqn. (4) to rewrite Eqn. (3) as the linear reduced form equation:

$$x_{it} = \mathbf{z}_{1it}\delta_1 + \mathbf{z}_{2it}\delta_2 + \bar{\mathbf{z}}_i\lambda + v_{2it} \tag{5}$$

where $v_{2it} = a_{2i} + u_{2it}$. Fourth, we assume that $(u_{1it},\ u_{2it})$ has a bivariate normal distribution with mean zero and is independent of $\mathbf{z}_i$. This assumption allows us to write the error term in Eqn. (2) as a function of the error term in Eqn. (3):

$$u_{1it} = \theta u_{2it} + \epsilon_{1it} = \theta(v_{2it} - a_{2i}) + \epsilon_{1it} \tag{6}$$

where $\theta = \frac{\mathrm{Cov}(u_{1it}, u_{2it})}{\mathrm{Var}(u_{2it})}$ and ϵ_{1it} is an idiosyncratic error term free from serial correlation due to our first and second assumptions.

Given our four assumptions, we can rewrite Eqn. (2) as:

$$\begin{aligned} y_{it} &= 1[\mathbf{x}_{it}\beta + c_{1i} + \theta(v_{2it} - a_{2i}) + \epsilon_{1it} \geqslant 0] \\ &= 1[\mathbf{x}_{it}\beta + \theta v_{2it} + c_{0i} + \epsilon_{1it} \geqslant 0] \end{aligned} \tag{7}$$

where $\mathbf{x}_{it} = (\mathbf{z}_{1it}, x_{it}, y_{i,t-1})$ contains our data, $\beta = (\beta_1', \beta_2, \rho)'$ is a vector of coefficients to be estimated, and $c_{0i} = c_{1i} - \theta a_{2i}$ is the composite unobserved effect. By including v_{2it} we have controlled for the endogeneity of x_{it} in time period t. However, there may be feedback loops such that x_i in other time periods may affect y_{it}. Thus, while we have controlled for the endogeneity in x_{it} caused by the unobserved effect c_{2i}, we have not yet controlled for the unobserved effect c_{0i}.

To control for c_{0i}, we adopt an approach similar to that used in Eqn. (4). We assume the composite unobserved effect, c_{0i}, is independent of the initial condition, y_{i0}, and the exogenous covariates, $\mathbf{z}_i$, but not v_{2i}:

$$c_{0i} = \alpha\bar{v}_{2i} + a_{1i} \tag{8}$$

where $\bar{v}_{2i}$ is a vector of time averages. This final assumption regarding the independence of the initial condition and the composite unobserved effect allows us to rewrite Eqn. (7) as:

$$y_{it} = 1[\mathbf{x}_{it}\beta + \alpha\bar{v}_{2i} + a_{1i} + \epsilon_{1it} \geqslant 0]. \tag{9}$$

By including $\alpha\bar{v}_{2i}$ Eqn. (9) controls for the unobserved effects of c_{0i} and c_{2i} and is now free of endogeneity caused by unobserved heterogeneity.

We follow the two-step estimation procedure outlined in Giles and Murtazashvili (2013). First, we estimate Eqn. (5) using pooled OLS. We save the residuals, $\hat{v}_{2it}$, from this reduced form equation and calculate $\bar{\hat{v}}_{2i} = \frac{1}{T}\sum_{t=1}^{T}\hat{v}_{2it}$. Next we estimate our probit model in Eqn. (9) using the conditional MLE and including the residuals and their time averages as right hand side regressors. We bootstrap our standard errors because our second-stage regression includes first-stage residuals.

(b) *Identification of crop diversity*

The second potential source of endogeneity in our regression equation is a simultaneity problem in that poverty status may affect crop choice or vice versa. We control for the potential endogenous regressor by choosing instrumental variables which allow us to estimate Eqn. (3).

To identify crop diversity we use the distance from each village to the nearest agricultural cooperative interacted with the lag of household land per capita. [14] Agricultural cooperatives in Ethiopia are vital conduits for the dissemination of seed, technology, and information. Cooperatives also operate as a home base for extension agents. Given the evidence on the role extension agents have in technology adoption in Ethiopia (Asrat *et al.*, 2011; Di Falco *et al.*, 2011; Di Falco & Veronesi, 2013; Krishnan & Patnam, 2013), proximity to a cooperative is likely to be associated with crop choice. To account for potential nonlinearities in the relationship between distance to a cooperative and crop diversity we also include distance squared as an instrument.[15]

While distance to the nearest agricultural cooperative is likely to be correlated with crop diversity, proximity to a cooperative is likely to be uncorrelated with household characteristics, such as household poverty.[16] This is because of government policy to establish complete geographic coverage of rural areas by cooperatives. While cooperative location is not random, neither is the government's choice of location determined by village size, village wealth, or local land quality, let alone a household's poverty level. Among the 15 villages used in our study, four villages host agricultural cooperatives while three villages are more than 10 km from a cooperative.[17] Of the four villages with a cooperative within the village, two of these villages have poverty levels of over 60%. The other two villages with cooperatives have poverty levels below 20%. This suggests that having a cooperative within the village is not related to the level of poverty in a village, let alone a specific household's poverty status.[18]

To help identify household-level crop diversity, we interact the distance between the village and the agricultural cooperative with the lag of household land per capita. Our justification for this procedure is that nonlinearities exist in the relationship between the distance to cooperative and a household's ability to adopt a diverse crop mix. These nonlinearities are due, in part, to the size of a household's landholding. A household with little land, even if it is near a cooperative, may be more likely to focus production on staple crops for own-food consumption. Conversely, a neighboring household with large landholdings may be more willing and able to grow a diverse set of crops. This insight relies on a host of evidence that the ability of smallholder farmers to adopt new agricultural technologies, such as on-farm diversity, is related to farm size (Chamberlain, 2008; Di Falco, Bezabhi, & Yesuf, 2010; Jayne, Mather, & Mgheyi, 2010). Thus, we believe that by interacting the land per capita term with the distance to cooperative we will pick up on a households ability to utilize the information and services at the cooperative regarding crop choice.

We verify the validity of the our instrument by performing a simple falsification test: if the variable is a valid instrument, it will affect crop diversity, but it will not directly affect household poverty. To determine that our instrument is correlated with crop diversity, we estimate the reduced form Eqn. (5) as:

$$div_{it} = \mathbf{z}_{it}\delta_1 + AG_{it}\delta_2 + \bar{\mathbf{z}}_i\lambda + \mathbf{d}_t + \mathbf{v}_j * \mathbf{t}_t + e_{it} \tag{10}$$

where AG_{it} is a set of instruments based on the distance to the nearest government run agricultural cooperative, and $\bar{\mathbf{z}}_i$ are the time averages of the household variables in $\mathbf{z}_{it}$. Results from two specifications (distance interacted with lagged landholding and distance squared interacted with lagged landholding) are presented in columns (1) and (2) of Table 4. In the first specification our IV is not significant, but when we include the distance squared interaction term both IVs become significant. Therefore, in our subsequent analysis we use the specification in column (2) of Table 4 for our first-stage regression. We calculate the residuals and add them, along with their averages, as control variables in the binary response model.

To show that our lagged landholding interacted with distance and distance squared IVs satisfy the exclusion restriction, we test for their significance in determining household poverty status. Neither of our instruments are significant factors in determining the probability that a household is below the poverty line (see column (3) in Table 4). Thus, our instruments satisfy this simple falsification test: they are correlated with crop diversity while also being uncorrelated with household poverty status, other than through their effect on crop diversity.

(c) *Estimating the impact of crop diversity on poverty*

We estimate the dynamic binary response model for the probability that household i in village j falls below the poverty line at time t as:

$$\begin{aligned} pov_{it} = 1[&\beta_1 pov_{it-1} + \beta_2(pov_{it-1} * div_{it}) + \beta_3 div_{it} + \mathbf{z}_{it}\delta \\ &+ \mathbf{d}_t + \mathbf{v}_j * \mathbf{t}_t + u_i + \epsilon_{it} \geqslant 0] \end{aligned} \tag{11}$$

where pov_{it} is a binary indicator for whether the household is poor. A household's poverty status is affected by its poverty status in the previous period, pov_{it-1}, our measure of crop

Table 4. *First-stage regressions & Poverty status and distance to Ag coop*

Model	Dependent variable: diversity index		Dependent variable: poverty status
	(1)	(2)	(3)
Lag poverty status			0.146***
			(0.014)
Household size	−0.005***	0.005***	−0.046***
	(0.001)	(0.001)	(0.004)
Lag of land per capita	−0.002	−0.003	−0.047*
	(0.008)	(0.008)	(0.028)
Years of education	−0.003	−0.003	−0.0002
	(0.002)	(0.002)	(0.007)
Female headed household	−0.016**	−0.016**	0.047*
	(0.007)	(0.007)	(0.025)
Distance to Ag coop * lag land per capita	0.001	0.009*	0.025
	(0.001)	(0.005)	(0.015)
Distance to Ag coop^2 * lag land per capita		−0.001**	−0.001
		(0.0003)	(0.001)
Households	1,015	1,015	1,015
Observations	6,090	6,090	6,090
R^2	0.300	0.304	0.227

Note. Fully robust standard errors clustered at the household are in parentheses ($^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). Regressions include time averages of explanatory variables, year dummies, and interactions between village dummies and a time trend.

diversity, div_{it}, a vector of household characteristics, $\mathbf{z}_{it}$, year dummies, $\mathbf{d}_t$, and village time trends, $\mathbf{v}_j * \mathbf{t}_t$. Our approach allows us to address potential correlation between unobserved household heterogeneity, u_i, and the other covariates. We also control for endogeneity of crop diversity with our village-level instrument interacted with the lag of household-level land per capita.

In applications similar to ours, Wooldridge (2005) and Giles and Murtazashvili (2013) present a correlated effects model. The correlated effects approach relaxes the assumption that the unobserved heterogeneity is uncorrelated with the exogenous variables. However, the need to adopt a correlated effects model is not mandatory. We test for the existence of correlation in our errors by using a standard ANOVA test. We find that our error terms are free of serial correlation (p-value = 0.557) and so proceed with our empirical analysis as presented in Section 4(a).

To test the robustness of our results, we estimate our model across several specifications (see Table 5). First, we treat crop diversity as exogenous and show results from both the linear probability (LPM) and probit estimations. We next control for the potential endogeneity of crop diversity by introducing our instrumental variable and show results for both the LPM and probit control function (CF) implementations.

5. DISCUSSION

We estimate Eqn. (11) but first treat crop diversity as exogenous. We present estimation results from both the LPM and the probit model in columns (1) and (2) of Table 5. In these specifications the relationship between household crop diversity and household poverty is not statistically significant. However, the interaction of the diversity index and lagged poverty status is significant and negative.

We next treat diversity as endogenous and introduce the distance to cooperative instruments, which allow us to identify the relationship between changes in crop diversity and changes in household poverty status. Columns (3) and (4) in Table 5 present results for the LPM and the control function approach. In these specifications, the relationship between household crop diversity and household poverty is negative and significant at the 5% level. The upward bias in the coefficients when diversity is treated as exogenous indicates the need for an estimation strategy which permits the identification in a dynamic binary response model where there are endogenous regressors. This suggests an improvement on previous studies, which have often treated crop choice as exogenous (Baird & Gray, 2014; Bezu *et al.*, 2012; Bigsten & Tengstam, 2011).

As one might expect, the coefficients on lagged poverty are significant and positive in all specifications. Households that are in poverty in one period are more likely to remain in poverty in the next period. This indicates a strong persistence in poverty among the sample households that is robust to various specifications and estimation techniques. Here again, the exogenous models exhibit upward bias in their estimation of coefficients. Further, the endogenous LPM overestimates the effects of diversity, relative to the control function specification. This suggests that models which fail to explicitly control for the initial conditions problem overstate the importance of poverty persistence.

A somewhat surprising result from our models is that the interaction term between the diversity index and poverty status is not significant (see column (4) in Table 5). This suggests that changes in diversity do not disproportionately impact wealthy households compared to poor households. There are numerous examples in the literature regarding events that have heterogeneous effects on households and that such heterogeneity is driven by differences in household wealth levels. Giles and Murtazashvili (2013) find that households in poverty are

Table 5. *Poverty status and crop diversity (second stage)*

Model	Dependent variable: poverty status			
	Exogenous diversity index		Endogenous diversity index	
	LPM (1)	Probit (2)	LPM (3)	CF (4)
Lag poverty status	0.167***	0.466***	0.164***	0.424***
	(0.019)	(0.055)	(0.018)	(0.070)
Diversity index * lag poverty status	−0.163*	−0.479*	−0.149*	0.445
	(0.087)	(0.284)	(0.088)	(0.296)
Diversity index	−0.019	−0.183	−0.619**	−5.294**
	(0.062)	(0.225)	(0.308)	(2.162)
Household size	0.036***	0.115***	0.041***	0.159***
	(0.002)	(0.008)	(0.003)	(0.020)
Lag of land per capita	−0.078***	−0.248***	−0.058***	−0.168
	(0.019)	(0.081)	(0.022)	(0.115)
Years of education	−0.010***	−0.029	0.010***	0.028**
	(0.002)	(0.008)	(0.003)	(0.012)
Female headed household	0.036**	0.147***	0.021	0.014
	(0.015)	(0.047)	(0.017)	(0.080)
Number of households	1,015	1,015	1,015	1,015
Observations	6,090	6,090	6,090	6,090
R^2	0.44		0.44	
Log likelihood		−3,462		−3,406
Replications for bootstrapped errors	500	500	500	500

Note. Fully robust bootstrapped standard errors in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). Regressions include explanatory variables in each year, time averages of explanatory variables, year dummies, and interactions between village dummies and a time trend. We also include household random effects in each specification. Regressions (1) and (2) treat crop diversity as exogenous. Regressions (3) and (4) include first-stage residuals free of serial correlation and their time averages.

more likely to be impacted by growth in village migrant networks compared to households that are not in poverty. Thiede (2014) finds that rainfall shocks have a larger detrimental effect on poor households compared to wealthy households. Conversely, in our sample, we find no heterogeneous effects of crop diversity that can be attributed to differences in poverty status.

In Table 6 we present average partial effects (APEs) for both the exogenous and endogenous specifications of the LPM, probit, and control function approach. In most cases, APEs are averaged across both the cross-section of the covariates and time. However, due to the presence of the interaction term between the diversity index and lagged poverty status, calculation of the appropriate APEs requires some attention. The APE for lagged poverty status is calculated at the average across observed values of the diversity index in the data. To explore the effects of crop diversification on poverty persistence, we calculate the APE of crop diversity when lagged poverty status equals zero for all households, when lagged poverty status equals one for all households, and the average across the observed values of poverty status in the data.

Turning to our research questions, to answer our first question, regarding the relationship between crop diversity and poverty status, we focus our analysis on results from the control function approach (see column (4) in Table 6) since the model controls for both sources of endogeneity and therefore does not overestimate the values of the coefficients. We find strong evidence that increased diversity decreases the probability that a household will be below the poverty line. On average, a 10% increase in the crop diversity index reduces the probability of being in poverty by 17.5%. For our second research question, we find strong evidence that an increase in crop diversity increases the probability that a poor household will rise out of poverty and reduces the probability that a non-poor household will fall into poverty. Specifically, for a household already above the poverty line, we find that a 10% increase in crop diversity reduces the probability of falling into poverty by 16.9%. For a household already below the poverty line, we find that increasing diversity by 10% reduces the probability of remaining in poverty by 18.3%.

We also find that household size and years of education have a statistically significant relationship with poverty status. Household size has a positive relationship while years of education has a negative relationship. These results are unsurprising; households with more members are more likely to be in poverty than those with fewer members, while households whose head has more education are less likely to be in poverty than those with less education.

As additional robustness checks we estimate our preferred specification but change the underlying data. Table 7 presents APEs from our probit control function estimation using three different manipulations of our data. In row (1) we present, for purposes of comparison, our primary estimation results. In row (2) we present results using an alternative specification of our diversity index. Specifically, we exclude crops only grown by a single household in a village in a year. In row (3) we present results using the unbalanced panel. In row (4) we present results using a trimmed data set, where the top and bottom 1% of observations of the diversity index are removed. Compared to these alternatives, our primary results (using the balanced panel and our preferred diversity index) provide more conservative estimates of crop diversity's effect in reducing poverty.

Synthesizing these results, a clear trend emerges: increasing crop diversity for rural households can help to mitigate poverty, by both raising and keeping households above the poverty line. The key result is that households which grow a more diverse set of crops are less likely to be in poverty. Thus, agricultural diversification, not specialization, is associated with poverty reduction among households in our study.

Table 6. *Average partial effects of determinants of poverty status*

Model	Exogenous diversity index		Endogenous diversity index	
	LPM	Probit	LPM	CF
	(1)	(2)	(3)	(4)
Lag poverty status	0.145***	0.402***	0.143***	0.120***
	(0.014)	(0.042)	(0.014)	(0.016)
Diversity index when lag poverty = 0	−0.019	−0.183	−0.619**	−1.688**
	(0.062)	(0.225)	(0.308)	(0.716)
Diversity index when lag poverty = 1	−0.182***	0.663***	−0.769**	−1.830***
	(0.064)	(0.222)	(0.314)	(0.715)
Diversity index averaged	−0.028	−0.210	−0.628**	−1.754**
	(0.059)	(0.215)	(0.307)	(0.714)
Household size	0.036***	0.115***	0.041***	0.051***
	(0.002)	(0.008)	(0.003)	(0.006)
Lag of land per capita	−0.078***	−0.248***	−0.059***	−0.054
	(0.019)	(0.081)	(0.022)	(0.038)
Years of education	−0.010***	−0.029***	−0.010***	−0.009**
	(0.002)	(0.008)	(0.003)	(0.004)
Female headed household	0.036**	0.147***	0.021	0.004
	(0.015)	(0.047)	(0.017)	(0.026)
Number of households	1,015	1,015	1,015	1,015
Observations	6,090	6,090	6,090	6,090
Replications for bootstrapped errors	500	500	500	500

Note. Fully robust bootstrapped standard errors in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). We calculate the APEs of the diversity index in three ways: (1) when lagged poverty status equals zero for all households, (2) when lagged poverty status equals one for all households, and (3) averaged across the observed values of poverty status in the data. The APE for lagged poverty status is averaged across the observed values of the diversity index in the data. All other APEs are averaged across both the cross-section of the covariates and time.

Table 7. *Additional robustness checks of average partial effects of diversity index*

		Diversity index Lag poverty = 0	Diversity index Lag poverty = 1	Diversity index Averaged
(1)	Basic results	−1.688**	−1.830***	−1.754**
		(0.716)	(0.715)	(0.714)
(2)	Alternative diversity index	−2.700**	−2.918**	−2.800**
		(1.295)	(1.311)	(1.300)
(3)	Unbalanced panel	−1.775**	−1.951**	−1.855**
		(0.867)	(0.867)	(0.866)
(4)	1% Trim of diversity index	−2.100***	−2.176***	−2.135***
		(0.678)	(0.695)	(0.684)

Note. (1) reports, for purposes of comparison, the results found in column (4) of Table 6. (2) reports results of an alternative specification of the diversity index in which we exclude crops cultivated only by a single households in a village in a year. (3) reports results from the unbalanced panel of 1,522 households. (4) reports results from the unbalanced panel when we trim the top and bottom 1% of observations of the diversity index. Fully robust bootstrapped standard errors in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). APEs of the diversity index are calculated in three ways: (1) when lagged poverty status equals zero for all households, (2) when lagged poverty status equals one for all households, and (3) averaged across the observed values of poverty status in the data. Regressions include explanatory variables in each year, time averages of explanatory variables, year dummies, and interactions between village dummies and a time trend.

6. CONCLUSION AND POLICY IMPLICATIONS

In order to shed light on recent policies that encourage crop diversity we adopted a recently developed dynamic binary response model that controls for state dependence, unobserved heterogeneity, and endogeneity of diversity. This approach represents an improvement over previous studies which have failed to control for potential simultaneity in the relationship between crop choice and household poverty, as well as selection bias in the diversity index.

Results from our empirical strategy provide much needed evidence in support of recent policies designed to encourage crop diversification by smallholder farmers. We find that growing a diverse set of crops decreases the probability of being in poverty. Furthermore, increased crop diversity reduces the probability that a household will remain in poverty or will fall into poverty in the future. We conclude that agricultural diversification, not specialization, is associated with poverty reduction among surveyed households. These results do not disproportionately impact wealthy households compared to poor households but are consistent across wealth levels.

Our conclusions help to elucidate a potential path out of poverty for the rural poor. Although the motivating factor to diversify may not be clear, and may range from a general desire to mitigate risk to a method of adaptation to climate change, it is clear that the specific economic and agronomic environment in Ethiopia means that diversification can reduce household poverty. Policies should be directed to encourage and increase household-level crop diversity, rather than to promote specialization in a small set of cash crops. In the case of Ethiopia, this means a greater focus on biodiversity and a lesser focus on encouraging households to specialize in cash crops such as coffee, sesame, or chat. Because the interaction term between the diversity index and lagged poverty status is not significant, we conclude that such policies will not have a disproportionate impact on one group over another. Therefore, actions taken to encourage crop diversity will generally be beneficial to all households; those which are presently in poverty will improve their probability of moving out of poverty, and those who are presently not in poverty will improve their probability of staying out of poverty.

Understanding the effects of household cropping decisions on poverty is an important first step in developing effective policies for household risk management. In generating strategies to address rural poverty, promoting and extending services which encourage crop diversification should be an important component. Ultimately, our research provides clear, quantitative evidence in support of policies that attempt to help households mitigate food insecurity and adapt to climate change through diversification of crop production. This is because such policies may create additional co-benefits by directly reducing poverty.

NOTES

1. Two recent studies, utilizing sound identification strategies, seek to provide evidence on the role of crop diversity in household welfare (Birthal, Roy, & Negi, 2015; Qin & Zhang, 2016). However, neither of these studies is interested in crop diversity itself as a poverty alleviation strategy. Birthal *et al.* (2015) use the concept of diversification as cultivation of high-value crops (HVCs) in India. The pathway of impact is not diversification but cultivation and sale of HVCs to high-income urban markets. In the limit, households should specialize in HVCs for sale to these urban markets. Qin and Zhang (2016) observe that households in China which specialize in crop production are less poor. But similar to Birthal *et al.* (2015), this is not due to specialization (or a lack of diversification), per se. Rather, as Qin and Zhang (2016) show, it is due to road proximity, allowing households to specialize in HVCs for sale to markets. In contrast to these studies, we examine diversification across all crops and are agnostic regarding whether specialization in HVCs for market or diversification to manage production risk (as just two examples) will be welfare maximizing for households.

2. Diversity could be measured in numerous different ways and may encompass not just crop choice but on- and off-farm activities. Recent examples of diversity measures in the literature include diversity of income (Barrett, Reardon, & Webb, 2001), diversity of genetic stock (Di Falco & Chavas, 2009), and diversity from cultivation of both staple crops and HVCs (Birthal *et al.*, 2015).

3. Mansanjala (2006) identifies three additional pathways through which cash crop specialization can lead to poverty alleviation. First, cash cropping may result in benefits to nonparticipants, through labor markets.

Second, cash cropping may contribute to the development of rural financial markets through relaxed credit constraints. And third, cash cropping is typically associated with improved agricultural technology and may be positively associated with increased productivity in other household activities.

4. Goetz (1993) identifies an additional constraint that may limit the benefits from specialization. In order for households to earn more income from cash crop sales than own-food production functioning markets must exist. If there is no reliable or regular market for the crops, and no insurance markets, transaction costs will remain high and crop specialization may not be profit maximizing.

5. This literature can be further divided into two subsets: studies which focus on the relationship between diversity and risk and studies that focus on the relationship between diversity and poverty. Numerous seminal studies have focused on the relationship between risk and diversity. These include Rosenzweig and Binswanger (1993), Alderman and Paxson (1994), Dercon (1996), Little, Smith, Cellarius, Coppock, and Barrett (2001), and Di Falco and Perrings (2005). We focus on the less studied relationship between diversity and income.

6. Attrition in the data set across the 15 years is 22.5% or 1.5% a year. We consider using an unbalanced panel, and do so as a robustness check. However, we are unable to reject the null that attrition in the data set is non-random. Over the six survey years t-tests of mean values for attriters and nonattriters show a statistical differences in terms of characteristics of household head (gender, education) and household characteristics (landholding, household size). There is also a statistical difference in means for our crop diversity term. The only variable where attriting and nonattriting households are statistically indistinguishable is in poverty status. We also estimate a probit using our variables of interest to predict attrition. Attriting households are smaller, more specialized, have more land and more education, and are more likely to be female-headed. While attrition does not appear to be random, there is no evidence that attrition is based on household poverty status.

7. While the ERHS includes a rich set of household characteristics and agricultural production variables, income and expenditure data are problematic. Previous research using the ERHS has noted that income data is generally underreported. While underreporting of income is a common feature of surveys in developing countries, Bezu *et al.* (2012) note that underreporting in the ERHS is severe. Average household consumption expenditure per adult equivalent is $125 while household income per adult equivalent is $68. (Income and expenditure are given in USD at 2000 constant prices). Additionally, income data were collected at four-month intervals which do not perfectly align with growing seasons, resulting in a greater likelihood of measurement error for households engaged in seasonal employment. This issue is especially acute for the 1997 round which, unlike the other rounds, was collected in the immediate post-harvest period. Due to the issues with household income data, many studies using the ERHS rely on consumption expenditure data or a consumption based poverty indicator to determine household well being (Bezu *et al.*, 2012; Dercon & Christiaensen, 2011; Dercon, Gilligan, Hoddinott, & Woldehanna, 2009).

8. Additional details on the specifics of each consumption bundle and the various sources of price data can be found in Dercon and Krishnan (1996), Dercon and Krishnan (2003), and Dercon *et al.* (2009).

9. This results is driven almost exclusively by single-year changes in two different villages. One village had a large increase in diversity while it also experienced a jump in village-level poverty. The other village saw a large decrease in village poverty at the same time households became more specialized in crop production. Excluding these outliers and redrawing the graph results in no significant correlation between changes in village-level poverty and changes in diversity.

10. Common alternatives in the ecology and economics literature are the Shannon index and the Herfindahl index (alternatively called the Simpson index). These indices measure diversity in terms of share or proportionality instead of simple count. In the case of crop production, an obvious alternative to our index would be to use either the Herfindahl or Shannon index and the area planted to each crop. However, constructing the index in this way would result in severe measurement error coming from self-reported land measures. Recent literature shows that the size of smaller farmed plots tends to be over estimated while the size of larger farmed plots tends to be underestimated (Carletto, Savastano, & Zezza, 2013, 2015). Thus, an index which uses area planted as the input would systemically overestimate diversity since households would overestimate the area planted in minor crops and underestimate the area planted in major crops. We do however verify that our results are robust to the use of these alternative indices. Our primary results do not change when using the Shannon index. We find that the Herfindahl index has no statistically significant relationship with poverty. These results are available from the authors upon request.

11. Ethiopia exhibits distinct agronomic zones: the highlands and the lowlands. The highlands are distinguished by steady rainfall and plateaus which are conducive to a variety of crops, while the lowlands generally have shallow soils, little rainfall, and more limited crop choices (Pankhurst, 2009).

12. We have tested alternative specifications of the index, including only staple crops; including only staple crops and cash crops; including livestock in addition to staple, cash, and tree crops. We also test a specification that excludes outliers by removing crops which are only cultivated by a single household in the village in a given year. Our results do not change significantly with these alternative measures. We include regression results from just one of these many alternative measures as a robustness check in the paper. Additional results are available from the authors upon request.

13. The model developed by Giles and Murtazashvili (2013) allows for serial correlation in the error terms. We test for serial correlation and fail to rejected the null of no serial correlation. Thus we proceed with this simplified model.

14. We believe the use of distance to an agricultural cooperative is an improvement on instruments used in other recent studies of agricultural households and adaptation strategies (such as crop diversification) in Ethiopia (Asrat, Berhane, Getachew, Hoddinott, Nisrane, & Taffesse, 2011; Di Falco *et al.*, 2011; Di Falco & Veronesi, 2013; Krishnan & Patnam, 2013). In order to control for potential endogeneity in the relationship between adaptation strategies and outcome, Di Falco *et al.* (2011) and Di Falco and Veronesi (2013) use extension services. They argue that use of extension services is correlated with the decision to choose an adaptation strategy but is not correlated with the outcome of the strategy (output or revenue). We feel that correlation may exist between unobserved household characteristics (and therefore poverty) and the propensity to take advantage of extension services. If such a relationship exists, extension services would no longer be a valid instrument for agricultural diversity. Therefore, we prefer distance to agricultural cooperatives as an instrument over the more commonly used extension services instrument.

15. We test several specifications for our instrument, including higher order terms (cubed, quartic), but found these terms provided no additional explanatory power.

16. The correlation coefficient for distance to coop and poverty is 0.088.

17. Some slight variation exists in distance over time as the Ethiopian government increased the spatial coverage of agricultural cooperatives. In cases where distance changed during 1994–2009 the distance always decreased.

18. As an added precaution against the possible correlation between government placement of agricultural cooperatives and village policies that may affect poverty we include village-time trends. These control for unobserved features in the village that may have affected placement of cooperatives.

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APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.worlddev.2016.08.011.