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Prevalence, economic contribution, and determinants of trees on farms across Sub-Saharan Africa

Daniel C. Miller [a,*], Juan Carlos Muñoz-Mora [b], Luc Christiaensen [c]

[a] Department of Natural Resources and Environmental Sciences, University of Illinois, Urbana, IL 61801, United States
[b] Department of Economics and Management, Pompeu Fabra University, C/Ramon Trias Fargas 25-27, Barcelona 08005, Spain
[c] Luc Christiaensen, The World Bank, 1818 H St NW, Washington, DC 20433, USA

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ABSTRACT

Trees on farms are often overlooked in agricultural and natural resource research and policy in Sub-Saharan Africa. This article addresses this gap using data from the Living Standards Measurement Study-Integrated Surveys on Agriculture in five countries: Ethiopia, Malawi, Nigeria, Tanzania, and Uganda. Trees on farms are widespread. On average, almost a third of rural smallholders grow trees. They account for an average of 17% of total annual gross income for tree-growing households and 6% for all rural households. Gender, land and labor endowments, and especially forest proximity and national context are key determinants of on-farm tree adoption and management. These new, national-scale insights on the prevalence, economic contribution and determinants of trees on farms in Africa lay the basis for exploring the interaction of agriculture, on-farm tree cultivation, and forestry to gain a more complete picture of the dynamics of rural livelihoods across the continent and beyond.

1. Introduction

In Africa, as in many other parts of the world, trees on farms are often overlooked in research and policymaking. In forestry, the focus is mostly on trees in forests rather than outside them (Barton, 2002; Fay and Michon, 2005). In agriculture and livelihood studies, the focus is typically on annual crops and their effects on household income. When perennials (such as coffee trees) are considered, it is mostly from a value chain perspective. The organization of extension and other services reflects this division, with agriculture and forestry typically separated in different institutions (de Foresta et al., 2013). As a result, trees on farms are often not included in forest-related, agricultural and livelihood statistics and little remains known about their prevalence and economic contribution, particularly at the national scale.

Yet trees on farms, which may range from sporadically occurring trees to areas dominated by a single tree crop through to large forest-like stands of trees, are often an integral component of broader agriculture-forest landscapes. They perform important ecological functions, including the provision of soil nutrients, prevention of soil erosion, habitat for animals, and greater structural connectivity (Manning et al., 2006; Place and Garrity, 2015) and serve as a key basis for biodiversity conservation (Bhagwat et al., 2008; Schroth et al., 2013) and climate change adaptation and mitigation (Mbow et al., 2014a). Sub-national case studies further suggest that on-farm trees often also provide a sizeable source of income (from timber or non-timber products such as fruit) (Degrande et al., 2006; Kalaba et al., 2010; Mbow et al., 2014b). Roughly, a third of the agricultural land in Sub-Saharan Africa is estimated to have had at least 10% tree cover during 2008–2010 (Zomer et al., 2014). Trees and agricultural activities therefore often co-exist not only in larger landscape contexts but also in single landowner holdings.

The available research on trees on farms has so far largely focused on case studies within particular countries (e.g. Dewees, 1995b; Godoy, 1992; Pouliot and Treue, 2013). Region-wide aggregated approaches have also shed light on the prevalence of on-farm trees (Zomer et al., 2014), but because they are based on remotely sensed data such studies have not directly accounted for household perspectives and practices. Cross-national (e.g. Poverty and Environment Network (PEN) studies highlighted in Wunder et al., 2014) and global (Agrawal et al., 2013) syntheses of forest and broader environmental income also exist, but systematic comparative information on the prevalence and economic contribution of trees on farms remains missing. This is especially problematic given intensifying competition for land in Africa (Peters, 2013) and the challenge of simultaneously advancing human development and environmental protection goals. The lack of reliable national-scale estimates of the prevalence and contribution of trees on farms increases the risk that they are left out of relevant policymaking processes, which

* Corresponding author at: Department of Natural Resources and Environmental Sciences, University of Illinois, S-406 Turner Hall, 1102 S. Goodwin Ave., Urbana, IL 61801, United States.
E-mail addresses: dcmiller@illinois.edu (D.C. Miller), juancarlos.munoz@upf.edu (J.C. Muñoz-Mora), lchristiaensen@worldbank.org (L. Christiaensen).

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could in turn result in greater priority for competing land uses that may undermine sustainability goals.

This article addresses this gap using nationally representative, geo-referenced household survey data from five African countries collected under the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) initiative. Together, these countries (Ethiopia, Malawi, Nigeria, Tanzania, and Uganda) represent 41% of the population in Sub-Saharan Africa and cover many of its agro-ecological zones. In addition to comprehensive household level information about consumption and income sources, these surveys also collected geo-referenced plot level information on the different crops and trees grown on each farm as well as the products harvested. These features of the data are exploited here to measure the prevalence and economic contribution of trees on farms in Sub-Saharan Africa, the first objective of this study.

The long time lag between planting and harvesting, insecure property rights, small plots and landholdings, and remoteness, which often characterize smallholder farming in Africa, would all seem to play against the adoption of trees. Yet case study evidence from across Africa also shows that small farmers do plant and manage trees on their farms. So, what are the key drivers? We begin to explore this question by estimating theoretically informed models of the determinants of on-farm tree adoption, the second objective of this article.

The article proceeds as follows. The next section reviews the empirical approach. Given the multitude of possible tree-like crops, it begins with a brief typology of the different trees considered. This is followed by a description of the data and methodologies used to measure and analyze their prevalence and contribution to overall household income and welfare. An empirical model is subsequently presented to estimate the key socio-economic and agro-ecological drivers of on-farm tree adoption, drawing on key insights from the literature. Section 3 discusses the findings. Concluding remarks are offered in Section 4.

2. Materials, methods, and theoretical underpinnings

2.1. Identifying and counting trees on farms

The nationally representative household surveys conducted under the LSMS-ISA initiative during 2010–12 from five African countries form the primary information base for this study.[1] LSMS-ISA household surveys have been stratified to be representative for rural and urban areas. The surveys gather a wide range of socio-economic information on households and the communities of which they are a part, with detailed attention to their sources of income and geo-referenced, plot-level information on their agricultural activities and crops grown.

Most importantly for this study, they also include detailed information for all cultivated plots about the type of crop (including tree crops), the harvest, and expenses incurred. For fallow or uncultivated plots, farmers were explicitly asked whether they contained trees. In countries where two seasons of agricultural data were collected (Malawi, Tanzania and Uganda), the average presence of trees across both seasons was taken. Across these countries a total of >20,000 rural households (and 47,000 plots) were surveyed and through application of survey sampling weights a representative portrait of on-farm tree prevalence and their economic contribution to rural household incomes was obtained.

In the absence of a standard classification of trees within crop data, potential trees were first identified from the LSMS-ISA agricultural crop production data, following the biological convention that to qualify as a tree a plant must be a woody perennial with a trunk or elongated stem that supports branches and leaves. With the help of several experts, the LSMS-ISA crop list was subsequently divided into five subcategories: (1) fruit trees (e.g. mango, orange, etc.); (2) tree cash crops (e.g. coffee, tea, etc.); (3) timber and fuelwood trees (e.g. Mahogany, bamboo, etc.); (4) plant/herb/grass/roots (e.g. maize, banana, etc.); and (5) a series of unidentified crops (e.g. wechino, etc.) (Table A.1 includes a detailed list of all the crops considered as trees and their further classification across these subcategories). The LSMS-ISA data included 230 crops in total, of which about 30% ($n = 68$) were classified as trees. Nearly all the remaining crops, as expected, fell in the plant/herb/grass/roots category.

Only the first three subcategories are considered here. While they contain all three perennials (with substantial lags between planting and harvesting which distinguishes them from other crops), they are nonetheless still quite distinct in their biological and economic features and support systems. Unlike fruit and timber trees, cash crops have been extensively studied in the development literature, for example, but not in forestry, and they are usually politically important and part of well-organized and integrated cooperatives and value chains. Unlike timber trees, fruit trees yield an annual return. This dramatically changes the parameters of the investment decision. For these reasons, we explore the three tree subcategories alongside each other.

The stock of trees on farms identified in our study likely represents a lower bound. First, home gardens are plausibly underreported as plots (and thus also trees in home gardens) and trees with no immediate productive function (e.g. shade trees, living fences, or those retained for their aesthetic value) may have been left out of household questionnaires. Second, respondents may not recall all trees on their lands or may be hesitant to report them where, for example, colonial legacies of state control of tree resources persist (Leach and Scoones, 2013; Ribot, 1999; Sendzimir et al., 2011). Lastly, the study was unable to classify a few species for which only the local name was available (Table A.1). Yet, such omissions would especially affect the number of trees reported, and not so much their incidence or the share of land allocated to trees (for each plot it is recorded whether trees are present or not). Consequently, this study focuses on analyzing the prevalence (i.e. presence or absence) of trees on farms and the share of land allocated to trees as opposed to the number of trees per se.

2.2. Contribution to household income and welfare

To examine the contribution of trees on farms to farmers' livelihoods, three indicators are examined: 1) how tree products are used (as a source of cash or mainly for own use or consumption); 2) their share in household crop and income portfolios (as an indication of their direct economic value) and 3) the consumption levels among farmers with and without trees on farms. Consumption levels also capture some of the more indirect contributions of trees on farms such as soil conservation, nitrogen fixing, and water regulation (Booth and Wickens, 1988; Nair, 2007; Place and Garrity, 2015) or as provider of organic fertilizer or fodder for livestock (at least to the extent that they raise and sustain agricultural income). None of these indirect aspects is typically addressed in the LSMS-ISA surveys (or household surveys more generally).

Information on the quantity of tree products harvested, their value (i.e. price per unit/kg), and their different uses (sale, auto-consumption, or other uses[2]) was directly obtained in all surveys, except in Tanzania. To assess their contribution to household income, we estimated the share of gross household income derived from trees on farms as part

[1] The LSMS-ISA initiative is a collaboration between the World Bank and national statistics offices in partner countries in Sub-Saharan Africa to design and implement multi-topic, nationally representative panel household surveys focusing on agriculture. This collaboration, funded by the Bill and Melinda Gates Foundation, seeks "to foster innovation and efficiency in statistical research on the links between agriculture and poverty reduction in the region" (World Bank, 2015). For details, see www.worldbank.org/lsms. Niger was excluded because, unlike other LSMS-ISA countries with available data for the study period, total income from trees or tree products was not recorded, only sales.

[2] "Other uses" denotes use as inputs into another production process (e.g. fodder for livestock, fruits for jam, timber for own house construction or fencing).

Table 1
Descriptive statistics.

	Ethiopia 2011–12			Malawi 2010–11			Nigeria 2010–11			Tanzania 2010–11			Uganda 2010–11		
	N	Mean	Std. dev.	N	Mean	Std. dev.	N	Mean	Std. dev.	N	Mean	Std. dev.	N	Mean	Std. dev.
Trees on farm															
Trees on farm (yes = 1)	3347	0.38	0.49	9936	0.22	0.42	2602	0.16	0.37	2621	0.55	0.49	1814	0.30	0.45
Fruit trees (yes = 1)	3347	0.17	0.36	9936	0.22	0.42	2602	0.06	0.23	2621	0.45	0.50	1814	0.05	0.21
Tree cash crops (yes = 1)	3347	0.33	0.48	9936	0.00	0.04	2602	0.15	0.36	2621	0.22	0.41	1814	0.27	0.43
Timber of fuel-wood (yes = 1)	3347	0.03	0.14	9936	0.00	0.04	2602	–	–	2621	0.18	0.42	1814	0.02	0.15
Share of farmland with presence of trees	3347	0.18	0.34	9936	0.00	0.04	2602	0.08	0.25	2621	0.41	0.42	1814	0.35	0.65
Share of farmland with presence of fruit trees	3347	0.05	0.19	9936	0.09	0.36	2602	0.04	0.17	2621	0.31	0.39	1814	0.05	0.26
Share of farmland with presence of tree cash crops	3347	0.17	0.33	9936	0.00	0.00	2602	0.07	0.23	2621	0.15	0.32	1814	0.32	0.63
Share of farmland with presence of trees for timber or fuel-wood	3347	–	–	9936	0.00	0.04	2602	–	–	2621	0.15	0.32	1814	0.02	0.16
Household controls															
Household size	3347	4.89	2.349	9936	4.70	2.19	2602	6.17	3.17	2621	5.34	3.18	1814	5.75	2.850
Number of children (<14 years old)	3347	1.78	1.505	9936	2.26	1.65	2602	2.82	2.29	2621	2.38	2.09	1814	2.97	2.106
Head's age (years)	3346	44.33	16.050	9936	43.14	16.47	2596	50.24	15.11	2620	47.52	16.05	1811	47.71	14.968
Head female (yes = 1)	3347	0.24	0.432	9936	0.25	0.43	2602	0.11	0.31	2621	0.23	0.42	1814	0.30	0.460
Head education (years)	3307	1.67	3.090	9913	5.11	4.10	2546	4.51	4.97	2569	4.98	3.92	1625	4.68	3.461
Assets and land															
Land owned (area - ha)	2854	1.78	3.64	9936	0.80	0.85	2573	1.00	1.84	2212	2.61	4.02	1658	1.66	3.14
Tropical livestock units (TLU)	3347	2.51	2.78	9936	0.44	1.86	2602	3.12	17.17	2621	1.53	3.30	1814	1.24	2.95
Geo-climatic variables															
Population density around 20 km (people/km^2) (2010)	3347	200.08	180.87	9936	183.86	159.76	2602	284.89	281.76	2586	93.14	132.65	1812	309.23	313.61
Tree cover % within 20 km (mean) (2010)	3347	51.45	20.44	9936	66.08	11.79	2602	34.86	23.68	2586	59.91	24.29	1812	65.90	15.67
Fertile soil % within 20 km (mean) (2010)	3347	0.73	0.27	9936	0.36	0.27	2602	0.53	0.31	2586	0.44	0.31	1812	0.20	0.23
Annual mean temperature (°C)	3347	18.42	3.18	9936	21.98	1.94	2602	26.36	0.99	2586	22.15	2.44	1812	21.79	1.86
Annual precipitation (mm)	3347	1175	340	9936	1094.36	258.43	2602	1382	617	2586	1068	326	1812	1234	187

Note: Statistics are for rural areas only and reported with sampling weight correction. "–" stands for missing information.

of gross agricultural and gross overall income.[3] Overall gross household income was calculated using the standardized definitions and methods developed under the Rural Income Generating Activities (RIGA) Project (Davis et al., 2010).[4] This approach facilitated comparison across countries. Production that had been consumed or stored was valued at unit values either derived from reported sales or, when absent, from median unit values at community or district levels (see Davis et al. (2010) for details). Other in-kind income was valued at market prices. A similar approach was followed to value (in-kind) income from on farm trees.[5]

Finally, as a broader, more encapsulating measure of the welfare effects associated with tree adoption and management, we compare average consumption levels among farmers growing trees on their farms with the consumption levels of those who do not grow trees on their farms, controlling for the characteristics of their environment. In particular, to do so real daily consumption per person (in 2011 purchasing power parity $) was regressed on whether the household had trees on farms or not and district fixed effects. The average difference in consumption is thus identified from the within-district difference in real daily consumption per person between tree and non-tree growing households

2.3. Correlates of on-farm tree adoption

At first glance, there appear few incentives for smallholder farmers to incorporate trees into their farming systems (Arnold and Dewees, 1997; Dewees, 1995a; Franzel, 1999; Godoy, 1992). There is a long time lag between planting and harvesting, while poor farmers are often liquidity constrained with a high discount rate. Access to (formal and informal) credit is limited, making it difficult to overcome the liquidity gap and poorer farmers often have smaller landholdings, necessitating attempts to generate revenues annually on all the land available to them. Insecure property rights further discourage investment in land improvement and trees, which only pay off over time. Outdated policies relating to state forest and tree management claims sometimes provide more disincentives for farmers to invest in trees on their land (Scherr, 2004). The role that these factors play will differ depending on the characteristics of the tree types. Timber trees only yield a benefit at the end of their lives for example, while fruit and cash crop trees yield an annual return. The institutional support available also differs widely across tree type as does the purpose of production (home consumption or sales).

Against this background, a number of hypotheses and empirical insights have been advanced in the literature. With respect to the effects of the demographic composition of the household, fruit trees, which have been associated with better nutritional status of household members, have been found to be more prevalent in female-headed households (Ickowitz et al., 2014; Meijer et al., 2015). Larger households,

[3] A more refined measure would be to calculate the share of net income from trees on farms over the total net income per household. However, complete expense data were not collected in all study countries and when collected, they were not collected at the crop level making it difficult to attribute costs to a particular crop. Importantly, the gross income ratio used here remains unbiased, under the assumption that the share of net over gross income is the same for income from trees on farms as for overall agricultural or total income. Put differently, to the extent that the share of expenditures on tree crop production to income from trees on farms is smaller than the share of expenditures on all agricultural production to income from agricultural production, the gross income from trees to gross agricultural income ratios reported here will be underestimates. A similar reasoning holds for the ratio of gross income from trees to overall gross income.

[4] Under this method, seven basic categories of household income are considered: (i) crop production; (ii) livestock production; (iii) agricultural wage employment; (iv) non-agricultural wage employment; (v) non-agricultural self-employment; (vi) transfer; and (vii) when available, other income sources like rental income, fishing or saving accounts. See Davis et al. (2010) for details.

[5] In a recent study, Angelsen et al. (2014) show that environmental and forest incomes can also be important in certain communities, especially those with closer access to forests. As in most standard household budget surveys, such income is not appropriately recorded in the LSMS-ISA data and has not been accounted for here either. A forestry module for LSMS-ISA and other national surveys has recently been developed to address this information gap (Bakkegaard et al., 2016).

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Table 2
Share of landholders with trees on their farms by category of tree (%).

Country	Percent of landholders with presence of any trees on farms	Percent of landholders with presence of fruit trees	Percent of landholders with presence of tree cash crops	Percent of landholders with presence of trees for timber or fuelwood
Ethiopia	38% (23.76% intercropped)	17% (23.73% intercropped)	33% (27.80% intercropped)	3%
Malawi	22% (16.05% intercropped)	22% (16.24% intercropped)	0.1% (0% intercropped)	0.1%
Nigeria	16% (85.91% intercropped)	6% (91.89% intercropped)	15% (86.67% Intercropped)	Not Available
Tanzania	55% (87.50% Intercropped)	45% (91.89% Intercropped)	22% (87.63% Intercropped)	18% (82.28% Intercropped)
Uganda	30% (95.59% Intercropped)	5% (99.66% Intercropped)	27% (96.59% Intercropped)	2% (77.89% Intercropped)
Overall average	30% (47.37% Intercropped)	20% (43.78% Intercropped)	12% (63.74% Intercropped)	3%

Note: All descriptive statistics corrected by sampling weight.

with more labor available, are also more likely to adopt tree-based cultivations, which is especially labor intensive in the early stages of tree planting and management (Dewees, 1994; Godoy, 1992). Better endowed households, on the other hand, are likely better placed to overcome liquidity and credit constraints and thus more likely to adopt agroforestry practices (Pattanayak et al., 2003). The amount of land owned is in this regard a well-established determinant of the presence of on-farm trees (Cattaneo, 2001; Dewees, 1995a). The presence of trees also interacts with livestock assets. Studies in different African countries suggest two different relationships: small livestock (e.g. goats and sheep) may be associated with greater presence of trees on farms while cattle may be seen as a competitor for space (Place and Garrity, 2015; Scherr, 1995).

Geographic, climatic and biophysical conditions further affect the degree of on-farm tree planting. Geographic location shapes the biophysical endowments and a household's comparative advantage in accessing markets, which in turn can influence incentives to adopt agroforestry practices (Pattanayak et al., 2003). Factors such as soil quality, slope of farmland, proximity to forest, among others, create conditions that are more or less conducive to grow and maintain trees. Generally, these biophysical factors have been less well studied in the agroforestry adoption literature and evidence on their effects remains mixed (Meijer et al., 2015; Mercer, 2004). Poor soil quality, for example, has been found to encourage adoption, but when soil quality is too poor, farmers may avoid planting trees (Pattanayak et al., 2003). The effect of the availability of nearby forest land is also likely to vary. Near forests, farmers may maintain certain valuable tree species on newly cleared land or they may want to create a full separation from the forest on such land. Alternatively, as availability of forest resources decreases, they may plant more trees to cope (Arnold and Dewees, 1995). Proximity to markets may also shape on-farm tree adoption by, for example, generating incentives to favor certain types of trees, especially those yielding perishable products like fruit (Godoy, 1992; Mercer, 2004; Pattanayak et al., 2003).

To explore the importance of these different factors in determining the presence and extent of trees on farms, the following regression model is estimated:

$$\text{TreesOnFarms}_{ivc} = \alpha_1 + \mathbf{HH}'_{ivc}\boldsymbol{\rho} + \mathbf{Assets}'_{ivc}\boldsymbol{\delta} + \mathbf{GeoClimate}'_{ivc}\boldsymbol{\gamma} + \sum_{k=1}^{5} \theta_k dT_k + \varepsilon_{ivc} \qquad (1)$$

where sub-index i refers to a household in village v in country c. To explore whether the factors affecting adoption and the factors affecting the extent of tree planting differ, Eq. (1) was run separately using

(i) A binary measure of presence or absence of any trees on a given household's landholdings (i.e. *Trees on farm* ($yes = 1$)) as the dependent variable; and

(ii) A continuous measure of the share of landholdings with presence of trees (i.e. $^{Area\ of\ plots\ with\ presence\ of\ trees\ (ha)}/_{Farm\ size\ (ha)}$).

The former was estimated using a probit model, the latter using OLS. Furthermore, because key factors determining the differences in tree growing strategies may vary across tree types (Degrande et al., 2006), the analysis was also replicated by type of tree (i.e. fruit trees, tree cash crops and trees for timber or fuelwood). Exploiting similarity in the design of the questionnaires, the data were pooled across countries. This enabled us to identify those socio-economic and agro-ecological factors that were generic across countries in affecting the adoption and extent of on-farm tree growing. Through the inclusion of country dummies a sense of the importance of country-specific factors (e.g. policies and institutions) is also obtained.[6] The country dummies also help control for measurement differences across countries. Shapley values, which provide a decomposition of the explained variance of the dependent variable (measured by R^2) by each group of control variables (Shorrocks, 2013), are also reported. This approach helps to understand the mean contribution of each dimension or group of variables to the overall model (i.e. share of R^2 explained by dimension). Standard errors account for household sampling weights.

To explore the effects of the household's human capital endowments ($\mathbf{HH}'_{ivc}\boldsymbol{\rho}$) the following variables were included: household size, number of children (<14 years old), age of household head, a dummy variable indicating a female headed household, and the level of formal education (in years) of the household head (Godoy, 1992; Pattanayak et al., 2003). To capture the effects of the household's physical capital ($\mathbf{Assets}'_{ivc}\boldsymbol{\delta}$), we included: (i) the size of the land owned (in hectares), and (ii) the number of tropical livestock units (TLU, an international standard equivalence scale for different types of livestock).

The set of geographic and climatic controls, $\mathbf{GeoClimate}'_{ivc}\boldsymbol{\gamma}$, included human population density, average percentage of tree cover within 20 km of each household, soil fertility, annual mean temperature (°C), and average annual precipitation. These control variables were constructed based on household standardized geo-coordinates, which were collected in the LSMS-ISA survey data.[7] Farm location was used as a centroid to construct several variables covering the area within 20 km. The average percent tree cover within a 20 km radius of each

[6] Alternative specification using models for each country separately were used as robustness check. Results were qualitatively equivalent. These results are available upon request.

[7] LSMS-ISA surveys provide a modified coordinate to protect household confidentiality, by introducing a random distortion of 0–5 km from the original location of the rural household. For more details on this type of method and its implications for statistical inference see Perez-Heydrich et al. (2013).

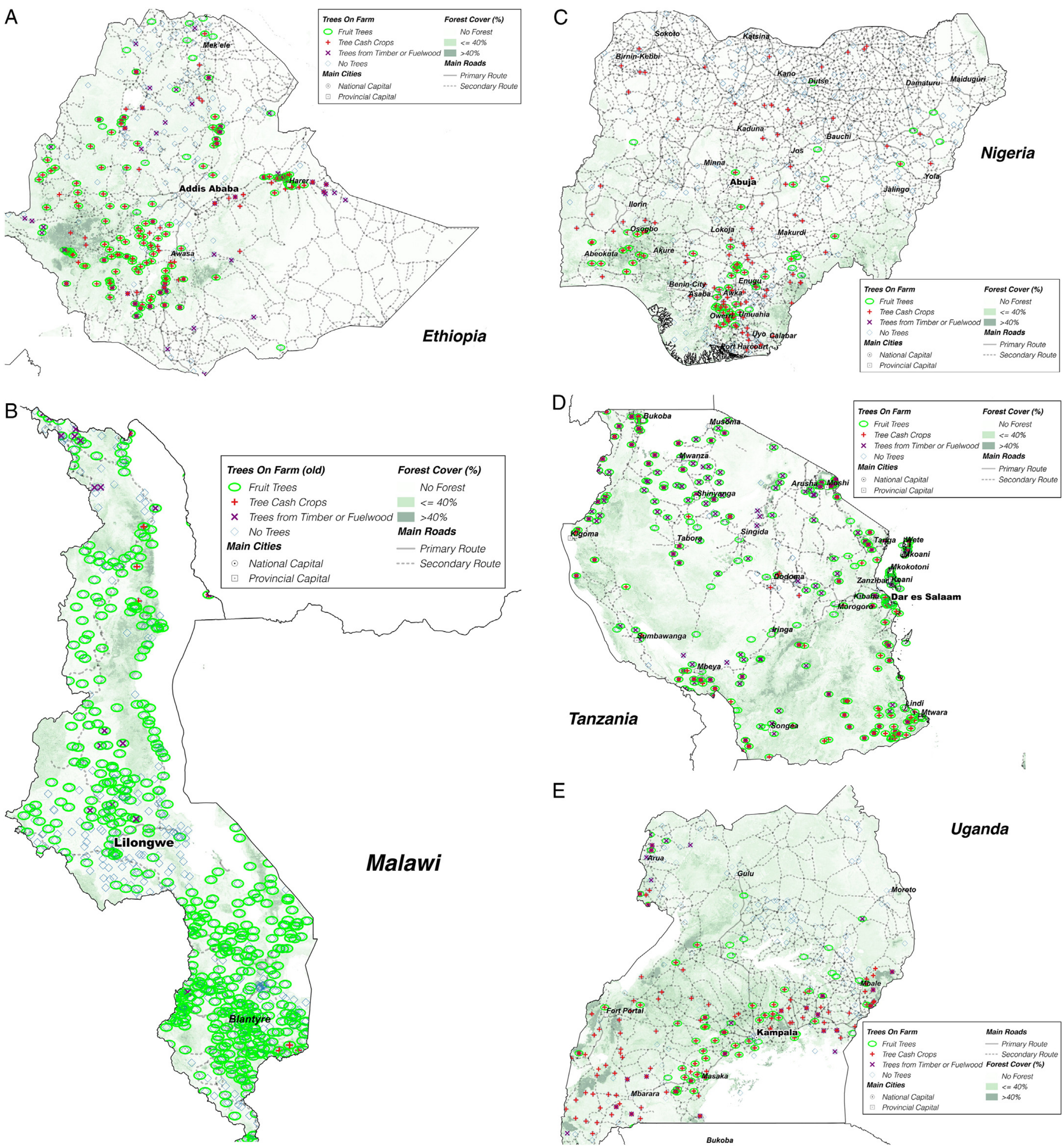

Fig. 1. Spatial distribution of households with presence of on-farm trees by tree type. Note: This figure shows the spatial distribution of trees on farms across the five study countries. Each map has a different scale depending on the country size. The geographical unit of analysis is the household. All statistics were corrected by sampling weight. Data Source: Authors' elaboration based on World Bank (2015).

household was derived using tree cover from MODIS Vegetation Continuous Fields (MOD44B) data (DiMiceli et al., 2011). An indicator of population density based on the number of people per km^2 within 20 km of each household was created using data from the Global Rural-Urban Mapping Population Project (Balk et al., 2006; CIESIN et al., 2011). To construct a variable on the average percentage of fertile soil within 20 km of each household, we combined information from the FAO/UNESCO Digital Soil Map of the World (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012) and Nunn and Puga (2010) estimates of percentage of land surface area with fertile soil.[8] Finally, we included two control variables—household specific measures of annual mean temperature (C) and average annual precipitation—which were created using a

[8] Defined as soil that is not subject to severe constraints for growing rain-fed crops in terms of soil fertility, depth, chemical and drainage properties, or moisture storage capacity.

standard methodology by the World Bank LSMS-ISA team and made available for all LSMS-ISA surveys (World Bank, 2015).

All models included a set of country fixed effects to account for country-level unobservables ($\sum_{k=1}^{5} \theta_k dT_k$). They were also rerun with district fixed effects, purging the estimated coefficients from potential unobserved district level variables (such as relative price differences across crops or market access). Table 1 summarizes the main descriptive statistics for all covariates.

3. Prevalence, economic contribution and determinants of trees on farms

3.1. About a third of smallholder farmers cultivated trees

Trees are clearly not marginal on the smallholder farms across the African countries studied: >30% of all rural households, on average, reported having at least one tree on their land (Table 2). Prevalence was highest in Tanzania (54%) and Ethiopia (38%) and lowest in Nigeria (16%). Further disaggregation by type of tree shows that Tanzanian farmers emphasize fruit trees (with 45% growing fruit trees, primarily mango, pawpaw (papaya), and oranges).[9] Tanzanian farmers also reported the highest prevalence of trees for timber (18%) and almost a quarter reported (23%) growing tree cash crops.

By contrast, in Ethiopia, <3.5% of landowners reported having trees for timber and fuelwood on their land, but the country had the highest proportion of farms with tree cash crops (32%), mainly coffee (65% of total tree cash crops) and chat[10] (34% of total tree cash crops), and 17% farmers reported growing fruit trees. The small share of on-farm timber trees is likely an underestimate as the presence of Eucalyptus was not captured in the questionnaires. Recent case studies (e.g. Bluffstone et al., 2015) found, for example, that 70% of households grew eucalyptus in the six districts they surveyed.

Uganda, which features much less land area in plantation forests, followed a similar pattern as Ethiopia, with few trees for timber or fuelwood reported and tree cash crops the most common type of tree (27%, nearly all of which (97%) are coffee trees). Few farmers reported growing fruit trees (bananas, which are prevalent in Uganda, are not classified as tree crops). In Malawi, fruit trees (mainly mango (56%) and pawpaw (12%)) were the most common category (22%). Information was incomplete on tree cash crops for Malawi, which may lead to an underestimate of the prevalence of trees on farms in that country. Only 0.01% of households reported having tree cash crops and among these households information about area planted and number of trees was missing. In Nigeria, tree cash crops comprised the most frequent category of tree found on farms, though information on timber and fuelwood trees was not available.

Almost 60% of trees on farms were reported in areas with other crops present (i.e. they are intercropped). However, this figure masks substantial variation (Table 2). Farmers in Malawi and Ethiopia intercropped much less than farmers in Nigeria, Tanzania, and Uganda. Only 10% of trees on farms were reported as present in the same area as other crops in Malawi, for example. In contrast, >95% of on-farm trees were reported as part of intercropped systems in Uganda. The common practice in that country and Tanzania of intercropping coffee with, for example, bananas is only part of the story and more detailed country-by-country study is needed to shed additional light on the dynamics of intercropping with trees. Our results lay the groundwork for such inquiry by highlighting the prevalence of agroforestry practices in the study countries.

Given the importance of agro-ecological conditions for tree growing, some spatial clustering of on-farm tree growing was expected. Statistically significant, though moderate spatial correlation among our observations was found (within country Moran's I was on average, 0.2) (Table A.2).[11] Clustering was especially clear for Tanzania and Ethiopia, two countries with high prevalence of trees on farms (Fig. 1; Table A.2). In Tanzania, households with tree cash crops (mainly cashew nut trees) were highly clustered in the southwest, suggesting spatial correlation with the presence of larger urban centers and seaports such as in Lindi. Ethiopia presents a similar pattern. There are few trees in the far east, which includes lower elevation land near Somalia, while landholders with fruit trees (46% of all households with trees on farms) were concentrated in the northwest and southwest of the country near some of Ethiopia's major population centers (e.g. Jimma and Bahir Dar). These patterns may be explained by the greater perishability of fruit and the constraints that farmers distant from ready access to markets face when trying to sell the fruits of their trees. Tree cash crops (e.g. coffee trees), on the other hand, were widespread and planted primarily in a mono-cropping system.

3.2. Trees on farms especially prevalent near forests

Households with trees on their farms are generally located close to forests in the LSMS-ISA study countries. The majority of tree-owning households were found within 10 km of forestland (at the 30% tree cover threshold) in all but one of the study countries (Nigeria; see Table 3). In those countries with the highest share of their land area covered by forest (Tanzania and Uganda), this rose to >85% of the households with trees on farms, on average. Even when using the more stringent forest cover threshold of 50%, these countries still had more than half of the households with trees on farms within 10 km of the forest areas (rising to 67% in Tanzania). Nigeria was at the lowest end of the spectrum with only 36% of its households with trees on farms located near forest areas at the less stringent 30% threshold. By contrast, Ethiopia had roughly the same overall forest cover (11% at the 30% threshold) as Nigeria, but more than half of its farms with trees were located within 10 km of a forest.

These findings suggest that farms with trees are important components of broader agriculture-forest landscapes in at least four of the five LSMS-ISA countries. Even in Nigeria more than a third of households with trees on farms were near forests. Our analysis of the different factors affecting on-farm tree adoption also shows the importance of distance to forest (see below). The proximity of on-farm trees to forests and the prevalence of intercropping across most of the study countries suggest substantial opportunities for more holistic, landscape-level approaches in policy and other practical efforts seeking to reconcile biodiversity conservation, climate change mitigation, and poverty reduction goals. Given the geographic and socio-economic diversity encompassed in our study countries, our results also suggest that such approaches may also be applicable in other countries across Africa as does the growing case study literature (e.g. Milder et al., 2014).

3.3. Contribution of trees on farms to rural livelihoods was non-negligible

Products harvested from trees on farms in the study countries were used mainly for self-consumption or sale (Fig. 2). The relative mix of these uses varied among the study countries. In Uganda, fruit tree products were used primarily for self-consumption, whereas in Malawi such trees served solely as a source of cash income. That fruit trees were used

9 Bananas were especially prevalent in Tanzania and Uganda, but they are classified under the category of plant/herb/grass/roots based on their biological characteristics.

10 Chat (*Catha edulis* (also known as khat or qat) is a is a slow-growing woody plant indigenous to the Horn of Africa and the Arabian Peninsula where it has been cultivated and used for centuries, primarily as a stimulant.

11 We employed the Moran's I Spatial Correlation index. This index provides an intuitive measure of correlation among nearby households in space. However, its absolute value may under-estimate the actual spatial correlation among households as it is based on geographical distances that ignore the sampling design of our data. Nonetheless, its statistical significance indicates that households with trees on farms tend to be closer to each other in space (i.e. clustered) than the other households in the sample.

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Table 3
Household distance from nearest forest defined as A) 30% tree cover threshold and B) 50% tree cover threshold.

Country	Extent of tree cover (ha) by country (2000)	Percent tree cover relative to country land area (2000)	Households in our sample (#)	Share (%) of households with trees on farms within		
				10 km of forest	20 km of forest	50 km of forest
A) 30% tree cover threshold						
Ethiopia	12,040,763	10.72	3347	55.81	73.91	93.3
Malawi	1,521,741	16.17	9936	85.87	100	100
Nigeria	10,033,216	11.13	2602	36.33	46.51	59.7
Tanzania	26,42,2567	29.85	2621	79.82	88.1	94.2
Uganda	7,768,069	37.83	1814	91.85	98.02	100
Overall	6,272,758	17.95	20,320	58.47	68.91	77.05
B) 50% tree cover threshold						
Ethiopia	5,426,282	4.83	3347	32.05	44.19	74.62
Malawi	313,115	3.23	9936	53.57	87.81	100
Nigeria	4,716,199	5.23	2602	20.17	29.27	42.53
Tanzania	9,702,599	10.96	2621	66.84	77.68	86.65
Uganda	3,271,840	15.94	1814	55.59	81.76	98.95
Overall	3,905,006	17.95	20,320	38.45	53.22	68.13

Note: To protect confidentiality household location coordinates in LSMS-ISA data are not exact, but rather based on a random distortion of 0–5 km. Data on extent of tree cover by country and percent tree cover relative to country land area derive from Hansen et al. (2013). Note that "tree cover" is not the same as "forest cover" in these data. "Tree cover" refers to the biophysical presence of trees, which may be a part of natural forests or tree plantations. Information on household distance to forest are based on the authors' calculations from LSMS-ISA data sets (World Bank, 2015) and "MOD44B MODIS Vegetation Continuous Field Coll. 5–2000 through to 2010: Percent Tree Cover" (DiMiceli et al., 2011).

significantly for self-consumption in countries like Uganda (and also Ethiopia) suggests that such trees may play an important role in household food security, as shown in a variety of contexts across Africa (Garrity et al., 2010). In the case of tree cash crops, production was mainly used for sale, as expected, though in Ethiopia a non-negligible share was also used for own consumption (linked to coffee consumption) and in Nigeria for other uses, such as for storage and gifts.

Turning to the contribution to total income, income from trees on farms contributed on average 6% of overall annual gross household income (i.e. taking farmers with and without trees on their farms together). The income share averaged 7% in Nigeria, 9% in Tanzania, 6% in Ethiopia and Uganda, but <4% in Malawi (Table 4). We note that estimates for Malawi may be low because information on tree cash crops was not provided in the LSMS-ISA survey data. For those households with trees on their farms the average contribution across the study countries was almost three times as much, i.e. 17% and about 32% as a share of agricultural gross income.[12] Surprisingly, the contribution of trees on farms to gross income among farmers with trees on farms, was highest in Nigeria (36%), even though tree growing occurred least frequently there, suggesting a high degree of specialization among tree growing households. At 18%, income from trees among households with trees on their farms was also significant in Uganda. Clearly, income from tree growing can be quite important, with the larger share typically coming from tree cash crops (14% of gross income among farmers with on-farm trees and 18% of gross agricultural income). Nonetheless, even though much less commented upon, income among fruit trees still contributed 5% of gross income and 16% of gross agricultural income.

Finally, taking a fully reduced form, we compared real per capita consumption levels (2011 PPP) among tree growing households and non-tree growing households controlling for district level effects (Table 5). As expected, tree cash crop growers were on average substantially better off (84% in Ethiopia, 19% in Nigeria, and 3% in Tanzania, though no difference was discerned in Uganda). Farmers with fruit trees on their farms were also better off in three of the five case countries (Ethiopia, Nigeria and Uganda). However, no positive effect was found for timber tree growing. Households with timber and fuelwood on their land appeared to be even worse off in Malawi. This result may be due to characteristics particular to the tiny (0.18%) subset of households reporting having such timber or fuelwood trees. Generally, it accords with other research that has found a significant overlap between areas of high poverty and high forest cover (sites for timber and fuelwood resources) across a large proportion of Malawi's territory (Sunderlin et al., 2008).

3.4. Gender, land and labor endowments, proximity to Forest and country factors drove on-farm tree growing

Table 6 presents the estimated effects of different correlates on the adoption of and land allocation to trees on farms. Tables A.3, A.4, and A.5 zoom in on the results by tree type. The model had little power in explaining the adoption of or land allocation to timber trees (Table A.5), but a number of clear generic patterns emerge when looking at the correlates of tree cash crops and fruit trees. First, adoption and land allocation to fruit trees and tree cash crops increases with the education level of the household head. Second, the adoption and land allocation to tree cash crops was about 5 percentage points less among female-headed households. This result is consistent with studies showing lower land tenure security among women in Africa (Berry, 1988; Schroeder, 1999) and the notion that women lack time for tree crop planting and management given their responsibilities for food crops and domestic chores (Berry, 1988). It also accords with studies showing how the limited availability of adult male labor can limit a given household's ability to include high value trees in their livelihood portfolio (Fisher, 2004). The negative correlation of on farm tree growing with female headship also holds for fruit tree crops, but is substantially less pronounced, consistent with the higher nutritional value of fruit trees (Degrande et al., 2006; Mbow et al., 2014b). Third, tree cash crops and fruit trees also tend to be more likely among households with older heads, consistent with other studies (Pattanayak et al., 2003) and the notion that it takes time for trees to grow and mature.

Fourth, land (but also labor) endowments also mattered, with larger farms (but also larger households) tending to grow more trees. Land

[12] By comparison, a recent cross national study of households living in or near forests found that natural forests in Africa contributed 21% to household incomes and plantation forests <1% (Angelsen et al., 2014).

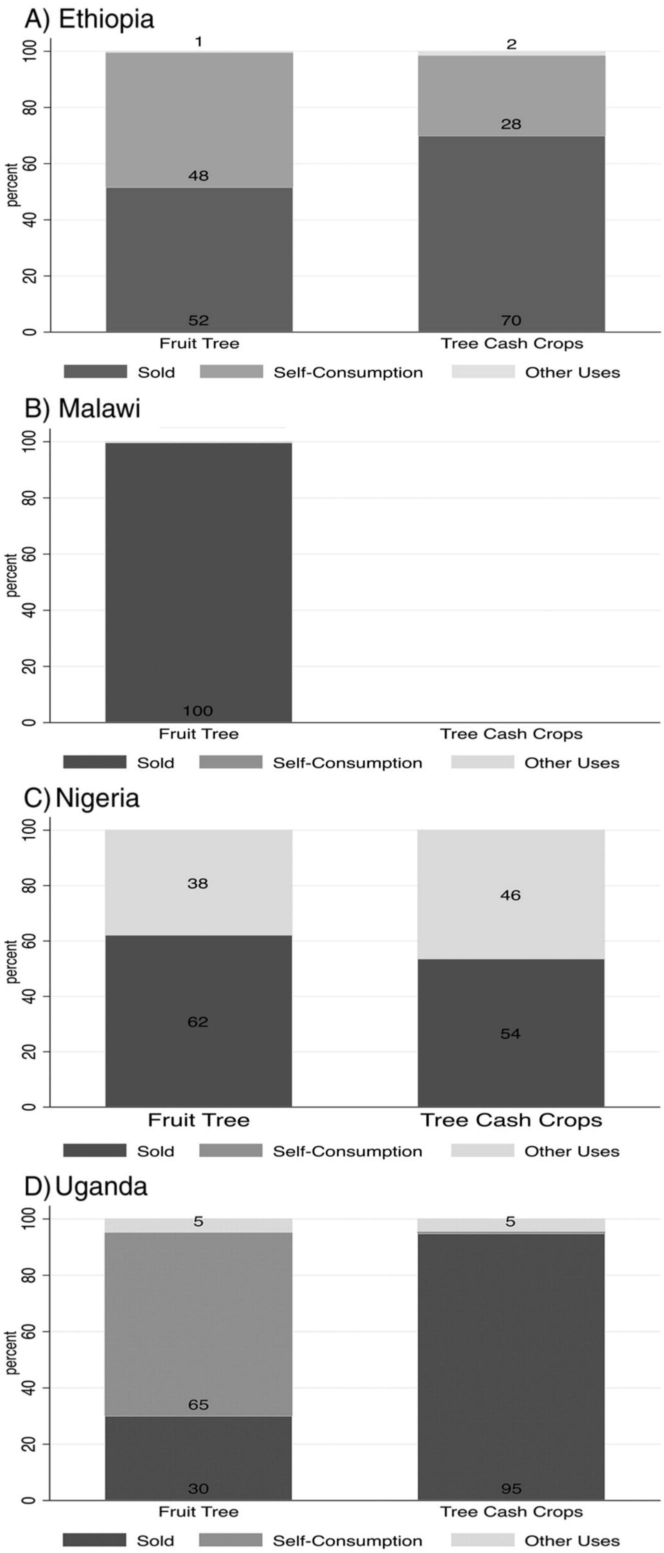

Fig. 2. Share of tree products by use, by country. Note: These figures show whether different categories of trees on farms were sold, used for self-consumption, or had other uses. Data were not available for Tanzania, as information on main uses for trees was not collected in that country. In Nigeria, the share of tree products for self-consumption was not collected. All statistics were corrected by sampling weight.

ownership was positively and significantly correlated with share of farmland with trees as expected. This result makes sense given the higher land intensity of tree crops.

Somewhat surprisingly, however, land ownership was not significant in the overall adoption model, but it was positively correlated in the fruit tree model (Table A.3).

Household size, an indicator of labor endowment, given that the number of children is controlled for, is positively associated with the adoption and allocation of farm land to trees (Table 6). The finding held separately for the fruit tree model, but not for the tree cash crops (Tables A.3 and A.4), suggesting that labor constraints may be more binding for fruit than tree cash crops. Adoption of fruit trees was also negatively correlated with ownership of livestock, a result consistent with studies showing that larger domestic animals (i.e. representing a greater number of TLUs) compete with trees on farmers' land (Place and Garrity, 2015; Scherr, 1995).

Fifth, the finding of more on-farm tree planting in forest rich environments was confirmed in the multivariate setting. While it might be argued that farmers would increase the density of trees on their farms as forest resources nearby decrease (Arnold and Dewees, 1995), they could also continue agroforestry systems which already have an integral relationship with nearby forests, including practices such as retaining key tree species during forest clearing (e.g. Brottem, 2011; Degrande et al., 2006). The empirical results here are more in line with the latter. On farm trees also tend to be more prevalent in environments where the temperature is higher. Overall, geo-climatic variables were important predictors, accounting for about 31% of the total variation in the adoption of trees on farms (Table 6). The strength of this result buttresses previous findings demonstrating that biophysical conditions are key drivers of farmer decisions to adopt and maintain trees on-farm (Pattanayak et al., 2003; Place and Garrity, 2015). Surprisingly, no systematic correlation was found across countries with population density (or soil fertility).

Finally, country fixed effects also explained an important share of the variation (>40% for adoption). This could partly reflect differences in survey design and implementation across the study countries. Although the World Bank has taken pains to ensure standard practice in the LSMS-ISA countries, some differences remain (e.g. omission of eucalyptus in Ethiopia). Other and plausibly more important, country differences relate to differences in national level policies and institutions. Forest and tree-related policies have for example been shown to play a decisive role in shaping whether farmers decide to adopt trees on their farms or not. In many countries, forest regulations create disincentives for on-farm tree management (Place and Garrity, 2015; Ribot, 1999) and changes to such regulations can spur changes in practice as shown in the recent re-greening in Niger, which has been catalyzed by political openings and reforms to colonial-era forest and rural policies that allowed local innovation in land management (Sendzimir et al., 2011). Among the case countries studied here, Tanzania stands out. Compared to the reference country, Ethiopia, where forest policy has remained more centralized (Ayana et al., 2013), policy relating to forests and trees in Tanzania has been more decentralized, with arguably a stronger emphasis on clearly defined tree tenure rights (Petersen and Sandhövel, 2001). Overall country governance quality may also affect farmer decisions vis-à-vis trees. For example, higher incidence of corruption, which may disproportionately affect the sale of high value tree products, is likely to provide a disincentive to invest in tree crops.

4. Concluding remarks

In this article we used nationally representative household-level data to explore and compare the prevalence and economic contribution of trees on farms across five African countries. Three main findings emerge. First, trees on farms are widespread across the continent and comprise a key component of agricultural-forest

Table 4
Contribution of trees on farms to annual gross household and agricultural income.

		Annual gross household income			Annual gross agricultural income		
		Contribution from trees on farm (%)	Contribution from fruit trees (%)	Contribution from tree cash crops (%)	Contribution from trees on farm (%)	Contribution from fruit trees (%)	Contribution from tree cash crops (%)
Ethiopia 2011–12	All farmers	5.55	0.14	5.80	8.41	0.35	8.61
	Only farmers with trees on farm	13.75	0.37	14.39	20.93	0.90	21.44
Malawi 2010–11	All farmers	3.32	3.32	0.00	20.32	20.32	0.00
	Only farmers with trees on farm	13.43	13.43	0.00	82.32	82.32	0.00
Nigeria 2010–11	All farmers	6.90	1.40	6.40	6.76	0.94	5.82
	Only farmers with trees on farm	36.20	7.92	33.31	36.14	5.28	30.86
Tanzania 2010–11	All farmers	8.82	4.02	4.05	14.27	7.84	5.30
	Only farmers with trees on farm	13.32	6.07	6.11	21.56	11.83	8.00
Uganda 2010–11	All farmers	5.94	0.32	5.73	7.31	0.61	6.90
	Only farmers with trees on farm	18.75	1.02	18.09	23.10	1.93	21.80
Overall	All farmers	5.98	1.80	5.33	11.05	5.51	6.81
	Only farmers with trees on farm	16.85	5.16	13.91	31.47	15.82	17.93

Table 5
Relationship of trees on farms and daily consumption per person.

		Dependent variable = Log. real daily consumption per person (in 2011 PPP)			
		(I)	(II)	(III)	(IV)
Ethiopia 2011–12	Trees on farm (yes = 1)	0.597*** [0.037]			
	Fruit trees on farm (yes = 1)		0.382*** [0.053]		
	Tree cash crops on farm (yes = 1)			0.612*** [0.039]	
	Trees for timber or fuelwood on farm (yes = 1)				0.132 [0.134]
Malawi 2010–11	Trees on farm (yes = 1)	0.000 [0.031]			
	Fruit trees on farm (yes = 1)		−0.006 [0.010]		
	Trees for timber or fuelwood on farm (yes = 1)				−0.323*** [0.103]
Nigeria 2010–11	Trees on farm (yes = 1)	0.212*** [0.035]			
	Fruit trees on farm (yes = 1)		0.252*** [0.046]		
	Tree cash crops on farm (yes = 1)			0.177*** [0.030]	
Tanzania 2010–11	Trees on farm (yes = 1)	−0.002 [0.030]			
	Fruit trees on farm (yes = 1)		0.011 [0.010]		
	Tree cash crops on farm (yes = 1)			0.032*** [0.011]	
	Trees for timber or fuelwood on farm (yes = 1)				0.010 [0.010]
Uganda 2010–11	Trees on farm (yes = 1)	0.010 [0.025]			
	Fruit trees on farm (yes = 1)		0.102*** [0.032]		
	Tree cash crops on farm (yes = 1)			0.002 [0.010]	
	Trees for timber or fuelwood on farm (yes = 1)				0.002 [0.021]

Note: Sampling weights and fixed effect were used for all regressions.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

landscapes. The East African countries of Tanzania, Uganda and Ethiopia had especially high incidence of trees on agricultural lands, with about a third to more than half of rural households reporting on-farm trees. Fruit trees and cash crop trees were the two most popular types of trees while trees for timber and fuelwood were much less prevalent (reported by 5% of respondents). The proximity of most households with trees on farms to forests and the high incidence of intercropping across the study countries suggest that on-farm trees are also an integral part of larger rural agricultural-forest landscapes. As elsewhere in the developing world (Sayer et al., 2013), policies and practices designed to improve the management of such trees in Africa therefore hold significant promise for helping to reconcile the sometimes conflicting goals of reducing rural poverty, conserving biodiversity, and mitigating climate change.

Our second finding is that trees on farms deliver non-negligible economic benefits to rural households. Across the rural population as a whole, production from trees on farms accounts on average only for 6% of total annual gross income. Yet, this increases to 17% on average for those households growing trees on their farms. By way of comparison, these results are similar to available evidence on forest and environmental income. For example, a recent study using national-scale data from Mexico (López-Feldman, 2014) found that forest and other environmental resources contributed 6.2% to total incomes for Mexican rural households. A global study focusing on those households living in or near tropical forests (Angelsen et al., 2014) concluded that income from natural forests and forest plantations accounted for 21% of total household income in Africa. Together, these studies suggest that trees—in forests and outside forests—provide non-negligible income to rural households in Africa, especially, but not only, to those living with trees nearby or on their land.

Finally, results from the analysis of the determinants of the adoption of and land allocation to trees on farms suggest the importance of national governance context and proximity to forests in understanding differences in on-farm tree growing. Country fixed effects accounted for >40% of the explained variation in the models. Given broadly similar sampling design and survey implementation in the collection of LSMS-ISA data and the fact that we controlled for the effect of other large-scale factors (e.g. climatic zone), governance and institutions likely comprise a large share of this national-level variation. Proximity to forests proved also an important predictor and

Table 6
Multivariate analysis of adoption and management of trees on farms.
Data source: Authors' calculations from LSMS-ISA data sets, World Bank (2015).

	Adoption analysis (Probit)			Determinants of share of farmland with trees		
	Dep. variable: trees on farms (yes = 1)			Dep. variable: share of farmland with presence of trees		
	(I)	(II)	Shapley value	(III)	(IV)	Shapley value
Household controls			0.011 (4.06%)			0.008 (2.76%)
Household size	0.008	0.012**		0.016**	0.012*	
	[0.006]	[0.005]		[0.007]	[0.007]	
Number of children (<14 years old)	−0.002	−0.004		−0.010	−0.007	
	[0.007]	[0.007]		[0.010]	[0.009]	
Head's age (years)	0.002***	0.002**		0.003**	0.004**	
	[0.001]	[0.001]		[0.001]	[0.001]	
Head female (yes = 1)	−0.055***	−0.060***		0.006	−0.023	
	[0.012]	[0.013]		[0.046]	[0.032]	
Head education (years)	0.003	0.004		0.010*	0.009*	
	[0.003]	[0.003]		[0.005]	[0.005]	
Assets and land			0.004 (1.51%)			0.206 (64.46%)
Tropical livestock units (TLU)	−0.003	−0.002		−0.001	−0.001	
	[0.002]	[0.002]		[0.001]	[0.001]	
Land owned (area - ha)	0.004	0.005		0.267***	0.263***	
	[0.004]	[0.004]		[0.094]	[0.094]	
Geo- and climate variables			0.033 (11.38%)			0.004 (1.28%)
Log population density around 20 km (people/sqkm) (2010)	0.086**	0.077***		0.166***	0.132***	
	[0.035]	[0.025]		[0.055]	[0.045]	
Tree cover % within 20 km (mean) (2010)	0.007***	0.007***		0.003	0.003	
	[0.002]	[0.002]		[0.003]	[0.003]	
Fertile soil % within 20 km (mean) (2010)	−0.004	−0.020		0.134	0.134	
	[0.072]	[0.075]		[0.151]	[0.147]	
Log. annual mean temperature (C)	0.027**	0.033***		0.045**	0.043*	
	[0.011]	[0.012]		[0.022]	[0.022]	
Log. annual precipitation (mm)	−0.000	0.000		−0.000	−0.000	
	[0.000]	[0.000]		[0.000]	[0.000]	
Country fixed effects			0.099 (33.87%)			0.075 (23.56%)
Malawi	−0.273***	−0.258***		−0.150	0.026	
	[0.043]	[0.026]		[0.128]	[0.135]	
Nigeria	−0.398***	−0.433***		−0.306**	−0.171	
	[0.061]	[0.055]		[0.131]	[0.134]	
Tanzania	0.124*	0.105		0.820***	0.715***	
	[0.063]	[0.069]		[0.146]	[0.118]	
Uganda	−0.262***	−0.270***		0.260	0.365*	
	[0.054]	[0.042]		[0.214]	[0.207]	
Mean dependent variable	0.290	0.290		0.243	0.243	
(Pseudo) R-squared	0.207	0.258		0.306	0.320	
Observations	18,907	18,907		18,907	18,907	
District/regional fixed effect	No	Yes		No	Yes	

Note: Baseline country is Ethiopia. Columns (I) and (II) present the point estimates for the adoption analysis (probit), where the dependent variable is the presence of any kind of trees on farm (yes = 1). Columns (III) and (IV) show results for determinants of share of farmland with trees (OLS), where the dependent variable is the share of farmland with presence of trees. District/sub-national regional fixed effects were included in one set of probit and OLS models, but not the other set. Robust standard errors in brackets, clustered at strata level. Sampling weights used for all regressions.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

formed part the broader set of geo-climatic variables, which accounted for about 30% of the variation. These findings suggest that further analyses focusing on specific countries or geo-climatic zones are needed to gain a deeper understanding of how such factors may drive farmer decision-making. The results from our cross-country study further indicate that households with larger landholdings tend to allocate more land to trees (both cash crop and fruit trees) and that female-headed households tend to be less engaged in tree growing, with the effect largest for tree cash crops. This latter finding may be linked to higher land tenure insecurity for female farmers and is consistent with the higher nutritional value of fruit trees. Country case studies are needed to shed more light on these general patterns.

Despite the already non-negligible prevalence and economic contribution of trees on farms that our study demonstrates, the numbers are likely still underestimates. The household data are unlikely to fully account for non-crop trees (e.g. for shade or different kinds of non-provisioning ecosystem services) and trees with no immediate productive function because they were not queried explicitly in the LSMS-surveys. The indirect effects of trees on farms on crops, livestock, and other productive activities are also very difficult to account for (Wunder et al., 2014) and information on them was not directly collected in the LSMS-ISA surveys. Ethiopia also presented a rare case where information on a key productive tree species—eucalyptus—was not collected.

Overall, the results suggest that trees on farms should be given more attention in agriculture, food security and poverty-related policy debates in Africa, particularly as the need to tackle climate change becomes more urgent. The data and analysis presented here provide a baseline for future benchmarking as well as building blocks for improving the information base relating to privately owned trees in Africa, including through improved data collection in future surveys. The open

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access LSMS-ISA surveys and other national survey data provide an important opportunity to do so. They deserve full support and could be strengthened in at least two ways: 1) by capturing the full range of relevant trees on farms, including those that may not have an immediate productive function, and 2) by including cost information in a way that facilitates comparison of income across LSMS-ISA countries. We were unable to include Niger in our analysis, for example, despite its status as an LSMS-ISA country and success in farmer managed natural regeneration and agroforestry (Garrity et al., 2010; Sendzimir et al., 2011) because income from trees on farms did not cover in-kind income from these trees, only income from sales.

The findings also point to several new avenues for exploring the interaction of agriculture, trees, and forests to better understand the dynamics of rural livelihoods in Africa and beyond. One area ripe for further exploration is the relationship between trees on farms and forest areas. Are trees on farms associated with more or less forest clearing? Why are households with trees on farms more likely to be located near forests? Panel data from LSMS-ISA surveys combined with newly available, high-resolution forest cover data make it possible to shed new light on these dynamics. Within specific countries it may also be possible to distinguish exotic from indigenous trees, which may be more likely to be retained when forest is cleared for agriculture. LSMS-ISA panel data also enable study of the economic contribution of trees on farms over time so as to understand the extent to which such trees can provide a means for farmers to escape poverty or achieve more enduring prosperity. Such panel data might also be fruitfully analyzed along with information on forest and tree-related institutions and policies in individual countries to better understand how these country-level variables may affect farmer decision-making relating to trees. Finally, we see significant scope for future research to collect and analyze information on the economic contribution not only of trees on farms, but also from forests and other wildlands to gain a more complete picture of the dynamics of rural livelihoods in Africa over time at the national scale.

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Appendix A. Appendix

Table A.1
Crop/tree classification by type of tree in LSMS-ISA data.
Data source: World Bank, 2015.

Crop	Type of tree	Crop	Type of tree
Agbono (Oro Seed)	Fruit tree	Black pepper	Tree cash crops
Apple	Fruit tree	Cashew	Tree cash crops
Avocado	Fruit tree	Castor beans	Tree cash crops
Bilimbi	Fruit tree	Chat	Tree cash crops
Bread fruit	Fruit tree	Clove	Tree cash crops
Buya	Fruit tree	Cocoa	Tree cash crops
Cherry (Agbalumo)	Fruit tree	Coffee	Tree cash crops
Cinnamon	Fruit tree	Dry leaves (Kuka)	Tree cash crops
Coconut	Fruit tree	Gum arabic	Tree cash crops
Custard apple	Fruit tree	Iyere	Tree cash crops
Date palm	Fruit tree	Locust bean	Tree cash crops
Durian	Fruit tree	Macadamia	Tree cash crops
Fig	Fruit tree	Monkeybread	Tree cash crops
Gishita	Fruit tree	Moringa	Tree cash crops
God fruit	Fruit tree	Oil palm	Tree cash crops
Grape fruit	Fruit tree	Palm kernel	Tree cash crops
Guava	Fruit tree	Ronier	Tree cash crops
Jackfruit	Fruit tree	Rubber	Tree cash crops
Kolanut	Fruit tree	Shea nuts	Tree cash crops
Lemon	Fruit tree	Tea	Tree cash crops
Lime	Fruit tree	Three leave yam	Tree cash crops
Malay apple	Fruit tree	Bamboo	Trees for timber and fuelwood
Mandarin/tangerine	Fruit tree	Black wattle	Trees for timber and fuelwood
Mango	Fruit tree	Fence tree	Trees for timber and fuelwood
Masau	Fruit tree	Firewood/fodder	Trees for timber and fuelwood
Oranges	Fruit tree	Kapok	Trees for timber and fuelwood
Paw	Fruit tree	Mahogany	Trees for timber and fuelwood
Peaches	Fruit tree	Natural forest trees	Trees for timber and fuelwood
Pear	Fruit tree	Other forest trees	Trees for timber and fuelwood
Plum	Fruit tree	Plantation trees	Trees for timber and fuelwood
Pomegranate	Fruit tree	Timber	Trees for timber and fuelwood
Pomelo	Fruit tree		
Pomme Du Sahel	Fruit tree		
Rambutan	Fruit tree		

(continued on next page)

Table A.1 (*continued*)

Crop	Type of tree	Crop	Type of tree
Star fruit	Fruit tree		
Tamarind	Fruit tree		
Walnut	Fruit tree		

Note: Crops included in LSMS-ISA surveys are not fully standardized, so there is variation across languages and local terminology for the same species in some cases. This table consolidates where possible such differences to present all tree types found in LSMS-ISA data used in this study.

Table A.2
Descriptive statistics on spatial distribution of households and plots with trees.
Data source: Authors' calculations from LSMS-ISA datasets, World Bank (2015).

Country	Average distance among households (km)	Average distance to nearest neighbor (km)	Spatial correlation index (Moran's I)			
			Number of plots with trees	Number of plots with fruit tree	Number of plots with tree cash crops	Number of plots with trees for timber or fuelwood
Tanzania	572.16 [301.65]	21.87 [19.72]	0.035***	0.025***	0.149***	0.105***
Ethiopia	687.90 [2141.28]	25.51 [19.13]	0.017***	0.026***	0.042***	0.025***
Uganda	272.41 [484.53]	12.01 [7.16]	0.005***	0.047***		0.041***
Malawi	259.66 [176.05]	12.96 [7.48]	0.035***	0.038***		0.012*
Nigeria	479.94 [250.42]	25.56 [16.97]	0.082***	0.090***	0.046***	
All countries	2277.7 [1673.77]	21.01 [16.79]	0.200***	0.279***	0.167***	0.124***

Note: This table presents spatial information and correlation index for key variables of interest. Average distance among households is the distance among all households included in the sample in kilometers (km). Average distance to nearest neighbor refers to the average distance between households in the same geographic area (i.e. community). Since information on type of tree is not available for all countries, there are some missing values for the spatial correlation index. Standard deviation in brackets. Two-sided null hypothesis reported.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.3
Multivariate analysis of fruit trees.
Data source: Authors' calculations from LSMS-ISA data sets, World Bank (2015).

	Adoption analysis (Probit)			Determinants of share of farmland with trees		
	Dep. variable: fruit trees on farm (yes = 1)			Dep. variable: share of farm area with presence of fruit trees		
	(I)	(II)	Shapley value	(III)	(IV)	Shapley value
Household controls			0.010 (3.63%)			0.010 (3.32%)
Household size	0.001	0.003		0.013*	0.012**	
	[0.003]	[0.003]		[0.006]	[0.006]	
Number of children (<14 years old)	−0.001	−0.002		0.003	0.002	
	[0.004]	[0.003]		[0.010]	[0.010]	
Head's age (years)	0.002***	0.002***		0.003***	0.003***	
	[0.000]	[0.000]		[0.001]	[0.001]	
Head female (yes = 1)	−0.020**	−0.020***		−0.047	−0.046	
	[0.009]	[0.008]		[0.028]	[0.028]	
Head education (years)	0.004*	0.005*		0.006*	0.006*	
	[0.003]	[0.003]		[0.003]	[0.003]	
Assets and land			0.003 (1.25%)			0.096 (59.30%)
Tropical livestock units (TLU)	−0.006***	−0.005***		−0.001	−0.001	
	[0.002]	[0.001]		[0.000]	[0.000]	
Land owned (area - ha)	0.005***	0.004***		0.088**	0.086**	
	[0.001]	[0.001]		[0.032]	[0.032]	
Geo- and climate variables			0.027 (9.60%)			0.006 (4.35%)
Log population density around 20 km (people/sqkm) (2010)	−0.000	0.000		0.000	0.001	
	[0.001]	[0.001]		[0.001]	[0.001]	
Tree cover % around 20 km (mean) (2010)	0.003***	0.003***		0.003**	0.003**	
	[0.001]	[0.001]		[0.001]	[0.001]	
Fertile soil % around 20 km (mean) (2010)	0.000	−0.000		−0.002	−0.003	
	[0.005]	[0.005]		[0.004]	[0.004]	
Log. annual mean temperature (C)	0.014***	0.018***		0.020**	0.021***	
	[0.005]	[0.003]		[0.008]	[0.006]	
Log. annual precipitation (mm)	0.000	0.000		−0.000	−0.000	
	[0.000]	[0.000]		[0.000]	[0.000]	
Country fixed effects (baseline country: Ethiopia)			0.084 (29.65%)			0.059 (36.81%)

Table A.3 (*continued*)

	Adoption analysis (Probit)			Determinants of share of farmland with trees		
	Dep. variable: fruit trees on farm (yes = 1)			Dep. variable: share of farm area with presence of fruit trees		
	(I)	(II)	Shapley value	(III)	(IV)	Shapley value
Malawi	−0.041	−0.038		−0.060	−0.036	
	[0.026]	[0.023]		[0.054]	[0.073]	
Nigeria	−0.211***	−0.245***		−0.131**	−0.114*	
	[0.031]	[0.017]		[0.063]	[0.064]	
Tanzania	0.159***	0.143***		0.556***	0.513***	
	[0.051]	[0.050]		[0.075]	[0.082]	
Uganda	−0.133***	−0.128***		−0.101	−0.080	
	[0.021]	[0.008]		[0.084]	[0.105]	
Mean dependent variable	0.207	0.207		0.159	0.159	
(Pseudo) R-squared	0.257	0.296		0.162	0.176	
Observations	18,907	18,907		18,907	18,907	
District/zone fixed effect	No	Yes		No	Yes	

Note: This table presents the multivariate results for fruit trees on farms. Robust standard errors in brackets, clustered at strata level. Sampling weights used for all regressions.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.4
Multivariate analysis of tree cash crops.
Data source: Authors' calculations from LSMS-ISA data sets, World Bank (2015).

	Adoption analysis (Probit)			Determinants of share of farmland with trees		
	Dep. variable: tree cash crops on farm (yes = 1)			Dep. variable: share of farm area with presence of tree cash crops		
	(I)	(II)	Shapley value	(III)	(IV)	Shapley value
Household controls			0.007 (2.70%)			0.006 (4.29%)
Household size	0.013*	0.012**		−0.003	0.002	
	[0.006]	[0.006]		[0.013]	[0.012]	
Number of children (<14 years old)	0.003	0.002		−0.012	−0.015	
	[0.010]	[0.010]		[0.009]	[0.010]	
Head's age (years)	0.003***	0.003***		0.002*	0.001	
	[0.001]	[0.001]		[0.001]	[0.001]	
Head female (yes = 1)	−0.047	−0.046		−0.055**	−0.052**	
	[0.028]	[0.028]		[0.025]	[0.023]	
Head education (years)	0.006*	0.006*		0.008**	0.009**	
	[0.003]	[0.003]		[0.004]	[0.004]	
Assets and land			0.001 (0.37%)			0.061 (44.08%)
Tropical livestock units (TLU)	−0.002	−0.002		−0.001	−0.001	
	[0.002]	[0.002]		[0.001]	[0.001]	
Land owned (area - ha)	−0.002	0.000		0.111**	0.112**	
	[0.003]	[0.003]		[0.043]	[0.044]	
Geo- and climate variables			0.084 (30.35%)			0.021 (15.24%)
Log population density around 20 km (people/sqkm) (2010)	−0.002	−0.002		−0.000	0.001	
	[0.001]	[0.001]		[0.001]	[0.001]	
Tree cover % around 20 km (mean) (2010)	0.007***	0.008***		0.007***	0.006***	
	[0.002]	[0.001]		[0.002]	[0.002]	
Fertile soil % around 20 km (mean) (2010)	0.012*	0.008		0.001	−0.003	
	[0.007]	[0.006]		[0.005]	[0.004]	
Log. annual mean temperature (C)	0.019**	0.020**		0.021	0.014	
	[0.009]	[0.009]		[0.015]	[0.014]	
Log. annual precipitation (mm)	−0.000	0.000		−0.000**	−0.000	
	[0.000]	[0.000]		[0.000]	[0.000]	
Country fixed effects (baseline country: Ethiopia)			0.11 (42.02%)			0.015 (10.85%)
Malawi						
Nigeria	−0.287***	−0.295***		−0.133	−0.037	
	[0.067]	[0.060]		[0.112]	[0.109]	
Tanzania	−0.198***	−0.205***		−0.074	−0.005	
	[0.043]	[0.028]		[0.101]	[0.083]	
Uganda	−0.189***	−0.191***		0.185	0.246	
	[0.041]	[0.025]		[0.183]	[0.168]	
Mean dependent variable	0.200	0.200		0.261	0.261	
(Pseudo) R-squared	0.192	0.263		0.122	0.141	
Observations	8994	8975		8994	8994	
District/zone fixed effect	No	Yes		No	Yes	

Note: This table presents the multivariate results for tree cash crops on farms. Robust standard errors in brackets, clustered at strata level. Sampling weights used for all regressions.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.5
Multivariate analysis of trees for timber or fuelwood.
Data source: Authors' calculations from LSMS-ISA data sets, World Bank (2015).

	Adoption analysis (Probit)			Determinants of share of farmland with trees		
	Dep. variable: trees for timber or fuelwood on farm (yes = 1)			Dep. variable: share of farm area with presence of trees for timber or fuelwood		
	(I)	(II)	Shapley value	(III)	(IV)	Shapley value
Household controls			0.009 (3.54%)			0.003 (1.75%)
Household size	−0.000	−0.001		−0.002	−0.012	
	[0.002]	[0.002]		[0.015]	[0.017]	
Number of children (<14 years old)	0.004	0.003		0.011	0.015	
	[0.003]	[0.003]		[0.013]	[0.013]	
Head's age (years)	0.001**	0.001***		0.001	0.002	
	[0.000]	[0.000]		[0.001]	[0.001]	
Head female (yes = 1)	−0.003	−0.004		0.077	0.048	
	[0.006]	[0.005]		[0.071]	[0.055]	
Head education (years)	0.001	0.002		0.001	−0.002	
	[0.001]	[0.001]		[0.005]	[0.005]	
Assets and land			0.001 (0.65%)			0.117 (52.21%)
Tropical livestock units (TLU)	0.000	0.000		0.017	0.011	
	[0.001]	[0.001]		[0.018]	[0.016]	
Land owned (area - ha)	0.001	0.001		0.143	0.144	
	[0.001]	[0.001]		[0.099]	[0.100]	
Geo- and climate variables			0.058 (20.73%)			0.009 (4.07%)
Log population density around 20 km (people/sqkm) (2010)	0.009*	−0.001		0.105	0.063	
	[0.005]	[0.004]		[0.066]	[0.047]	
Tree cover % around 20 km (mean) (2010)	−0.000	−0.000		−0.005*	−0.005*	
	[0.000]	[0.000]		[0.003]	[0.003]	
Fertile soil % around 20 km (mean) (2010)	0.024*	0.026***		0.418	0.331	
	[0.013]	[0.010]		[0.250]	[0.196]	
Log. annual mean temperature (C)	−0.004***	−0.003**		0.012	0.017	
	[0.001]	[0.001]		[0.015]	[0.015]	
Log. annual precipitation (mm)	0.000	0.000		−0.000	0.000	
	[0.000]	[0.000]		[0.000]	[0.000]	
Country fixed effects (baseline country: Ethiopia)			0.19 (70.22%)			0.024 (11.05%)
Malawi	−0.036***	−0.039***		0.308*	0.275	
	[0.005]	[0.004]		[0.168]	[0.168]	
Nigeria						
Tanzania	0.273***	0.178***		0.668***	0.473***	
	[0.065]	[0.050]		[0.194]	[0.152]	
Uganda	0.027	0.014		0.285*	0.201	
	[0.021]	[0.014]		[0.157]	[0.125]	
Mean dependent variable	0.032	0.032		0.115	0.066	
(Pseudo) R-squared	0.257	0.302		0.190	0.225	
Observations	16,392	16,361		16,392	16,392	
District/zone fixed effect	No	Yes		No	Yes	

Note: This table presents the multivariate results for tree for timber or fuelwood on farms. Robust standard errors in brackets, clustered at strata level. Sampling weights used for all regressions.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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