HIGH VALUE CROP COMMERCIALIZATION AND WOMEN'S EMPOWERMENT IN SUB-SAHARAN AFRICA: PANEL INSIGHTS REINFORCED BY DOUBLE MACHINE LEARNING AND QUASI-EXPERIMENTS

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TABLE OF CONTENTS

ABSTRACT

We examine how agricultural commercialization relates to women's empowerment across Ethiopia, Malawi, Tanzania, Uganda, and Nigeria using LSMS-ISA household panels (2010–2020), a modified A-WEAI (5DE), two-way fixed effects, Double Machine Learning, and propensity-score matched difference-in-differences. Entry into markets (extensive margin) is consistently associated positively with empowerment where identification is strongest: PSM-DiD shows noticeable gains when households begin selling any crops—especially in Ethiopia, Malawi, Tanzania and Nigeria—and positive correlations when existing sellers add cash crops to sales in Malawi (Ethiopia marginal). Intensive-margin analyses indicate that, holding commercialization constant, empowerment gains taper as the non-staple (cash-crop) share of sales rises in Ethiopia, Malawi, and Tanzania; effects are near zero in Uganda and Nigeria. Improvements concentrate in the income-decision domain, while workload risks emerge in some settings. A non-linearity test shows commercialization is positively associated with empowerment across sales-mix bands, with larger gains among producers with above average crop diversification that sell small and moderate amounts of non-staples, and smaller (still positive) gains when portfolios are mostly non-staples. Policy should (i) prioritize first-sale entry by investing in the "Hidden Middle" (local buying points, wholesale markets, 3PL/warehouse services) to cut fixed costs; (ii) program by diversification profile to avoid premature specialization; and (iii) institutionalize women's control over income flows (e.g., joint payment/account options) so market gains translate into durable agency.

Key words: Women's empowerment, high-value crops, non-staple crops, agricultural commercialization, market participation, difference-in-differences, panel data econometrics, causal inference, heterogeneous treatment effects, double machine learning.

RESUMEN EJECUTIVO

Examinamos cómo la comercialización agrícola se relaciona con el empoderamiento de las mujeres en Etiopía, Malawi, Tanzania, Uganda y Nigeria utilizando paneles de hogares LSMS-ISA (2010–2020), un índice A-WEAI modificado (5DE), efectos fijos de dos vías, aprendizaje automático doble (Double Machine Learning) y diferencias en diferencias con emparejamiento por puntaje de propensión (PSM-DiD). La entrada a los mercados (margen extensivo) se asocia consistentemente de manera positiva con el empoderamiento allí donde la identificación es más sólida: el modelo PSM-DiD muestra ganancias notables cuando los hogares comienzan a vender cualquier cultivo —especialmente en Etiopía, Malawi, Tanzania y Nigeria— y correlaciones positivas cuando los vendedores existentes añaden cultivos comerciales a sus ventas en Malawi (marginal en el caso de Etiopía). Los análisis del margen intensivo indican que, manteniendo constante la comercialización, las ganancias en el empoderamiento disminuyen a medida que aumenta la proporción de ventas de cultivos no básicos (comerciales) en Etiopía, Malawi y Tanzania; los efectos son cercanos a cero en Uganda y Nigeria. Las mejoras se concentran en el dominio de la toma de decisiones sobre los ingresos, mientras que en algunos contextos surgen riesgos relacionados con la carga de trabajo. Una prueba de no linealidad muestra que la comercialización se asocia positivamente con el empoderamiento a través de distintos rangos de

mezcla de ventas, con mayores ganancias entre productores con una diversificación de cultivos superior al promedio que venden cantidades pequeñas y moderadas de productos no básicos, y ganancias menores (aunque todavía positivas) cuando las carteras consisten mayoritariamente en productos no básicos. La política pública debería: (i) priorizar la entrada a la primera venta invirtiendo en el "intermedio oculto" (puntos de compra locales, mercados mayoristas, servicios de logística de terceros/3PL y almacenamiento) para reducir los costos fijos; (ii) programar según el perfil de diversificación para evitar la especialización prematura; e (iii) institucionalizar el control de las mujeres sobre los flujos de ingresos (por ejemplo, opciones de pago o cuentas conjuntas) para que las ganancias del mercado se traduzcan en una agencia duradera.

Palabras clave: Empoderamiento de las mujeres, cultivos de alto valor, cultivos no básicos, comercialización agrícola, participación en mercados, diferencias en diferencias, econometría con datos de panel, inferencia causal, efectos del tratamiento heterogéneos, aprendizaje automático doble.

I. INTRODUCTION

Agricultural commercialization—the transition from subsistence farming to market-oriented production—has been widely promoted as a pathway out of poverty for rural households in developing countries. However, this process has profound and often overlooked gendered dimensions. As agricultural systems transform, traditional gender norms, roles, and power dynamics within households may shift, potentially affecting women's agency, decision-making authority, and control over resources. While commercialization can increase household income, the distribution of benefits and decision-making power may not be equitable across gender lines, particularly when higher-value crops become involved.

Women's empowerment in agriculture represents a multidimensional concept encompassing various aspects of agency and opportunity. Following the framework developed by the International Food Policy Research Institute (IFPRI), we conceptualize empowerment as encompassing control over productive resources, decision-making authority, income management, and equitable time allocation. This approach allows for a holistic assessment of women's position within agricultural households beyond simplistic income-based measures.

The relationship between agricultural commercialization and women's empowerment presents a paradox. Economic theory suggests that increased market participation should enhance household welfare, potentially benefiting all members. Yet, extensive qualitative evidence across various contexts indicates that commercialization processes often favor men, particularly when focusing on high-value, non-staple crops. This gendered pattern has significant implications for agricultural development policies and programs aimed at improving livelihoods through market integration.

However, most of these qualitative articles are outdated (more than 15 years ago, some closer to the 90s), and could be part of a conventional wisdom that may not exist anymore (or to a lesser degree). On the other hand, quantitative studies are either solely focused on a single value chain, or lack a multi-country panel analysis. With this study, we provide up-to-date results (from the past decade to 2020 in most cases) for five SSA countries with a panel structure that spans an average of three survey waves.

1.1. Research Objectives and Questions

This paper aims to empirically investigate the relationship between agricultural commercialization—particularly the commercialization of non-staple[1] crops—and women's empowerment across five Sub-Saharan African countries: Ethiopia, Malawi, Tanzania, Uganda, and Nigeria. These countries represent diverse agroecological conditions, cultural contexts, and stages of economic development, allowing us to identify patterns across different settings.

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[1] We classify the following crop groups as non-staples: fruits, vegetables, oilseeds, permanent tree crops and industrial non-foods.

Our primary research question examines: *Is a higher share of non-staple crops in total agricultural sales negatively associated with women's empowerment, as suggested by qualitative literature?* We further explore whether this relationship varies across countries at different income levels, which may reflect varying stages of agricultural transformation and gender norm evolution.

Specifically, we test the hypothesis that as the share of non-staple crops in commercial sales increases, households are less likely to be categorized as "empowered" according to our modified Abbreviated Women's Empowerment in Agriculture Index (A-WEAI). This hypothesis is grounded in qualitative findings suggesting that when farming shifts toward higher-value cash crops, women often lose decision-making authority and control over income, as these crops are typically considered male domains.

Our analysis leverages the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) panel data, which provides a unique opportunity to employ fixed effects models that control for unobserved household characteristics. This methodological approach allows us to identify within-household changes in empowerment status as commercialization patterns evolve over time, moving beyond the cross-sectional associations that dominate the existing literature.

1.2. Contribution and Significance

This study makes several important contributions to the literature on gender, agriculture, and development. First, while numerous qualitative studies have documented how commercialization—particularly of high-value crops—can marginalize women's roles in agricultural decision-making, quantitative evidence using multidimensional empowerment measures remains severly limited and understudied. Most existing quantitative analyses focus on single dimensions of empowerment, such as income control or productive decisions in isolation, overlooking the interconnected nature of empowerment domains, while not explicitly addressing the association between crop commercialization and women empowerment, but rather focusing on single value chains, in specific regions within a single country, which may present realities that differ from the national trend.

Second, we develop and apply a modified version of the A-WEAI that captures four critical dimensions of empowerment: production decisions, resource ownership and access, income control, and time allocation. The group membership dimension was dropped and the weights equally redistributed, as the LSMS-ISA does not contain comprehensive information about individual group membership. This multifaceted approach provides a more comprehensive assessment of women's empowerment than commonly used unidimensional measures, allowing us to detect nuanced shifts in gender relations that might otherwise remain invisible.

Third, our multi-country panel analysis with household fixed effects enables us to isolate the relationship between changing commercialization patterns and empowerment dynamics over time, controlling for time-invariant household characteristics. By categorizing countries by income strata, we can also identify whether the relationship between commercialization and

empowerment varies with economic development levels, potentially revealing important contextual factors that moderate this relationship.

A key methodological innovation of our approach is the simultaneous examination of both overall commercialization and the composition of that commercialization within the same empirical model. Our specification allows us to disentangle: (1) the baseline association of agricultural staple crop commercialization on women's empowerment, and (2) how this relationship is modified by the share of non-staple crops in total sales. The sum of these components (when both are statistically significant) represents the total association on empowerment. This approach provides a more nuanced understanding than previous studies, which have typically focused on either overall commercialization or crop-specific effects in isolation, without considering how they interact (we also present a non-linear analysis regarding share of non-staples in total sales). Likewise, we employ two quasi-experimental strategies to assess women's empowerment. First, we treat the transition from subsistence to commercial farming as the intervention. Second, focusing on current crop sellers, we consider the introduction of high-value crops into their sales portfolio as the treatment.

Fourth, by distinguishing between staple and non-staple crop commercialization, we provide empirical evidence on whether the type of market engagement matters for gender outcomes. This distinction is crucial for agricultural development policies, which often promote high-value crop diversification without fully considering potential gender implications.

1.3 Integrating Machine-Learning Methods for Causal Econometrics

Over the past decade, applied econometrics has witnessed a rapid diffusion of machine-learning (ML) tools that move well beyond pure prediction and toward richer causal questions. Early syntheses by Mullainathan and Spiess (2017) and by Athey and Imbens (2019) argue that the flexibility of algorithms such as random forests, boosting, and deep neural networks can complement traditional identification strategies by modelling high-dimensional confounders non-parametrically, thereby reducing residual bias in treatment-effect estimation. Their core message—that ML should be viewed as an econometric ally rather than a competitor—has catalysed a new research agenda sometimes labelled causal machine learning.

A central contribution of that agenda is the double/de-biased machine-learning (DML) framework developed by Chernozhukov et al. (2018). DML orthogonalises both the outcome and the treatment with respect to a (potentially) high-dimensional control set using flexible ML learners and cross-fitting. Because the second-stage "de-biased" regression is constructed to be insensitive to first-stage regularisation error, the resulting estimators remain $\sqrt{n}$-consistent and asymptotically normal even when nuisance functions are learned with complex, non-parametric algorithms. Subsequent extensions have shown that DML can be paired with deep neural networks (Farrell, Liang, & Misra, 2021) and causal forests to recover heterogeneous treatment effects at scale (Wager & Athey, 2018).

Recent empirical work demonstrates the practical value of these methods in development and policy settings. For example, an Econometrics Journal reassessment of several canonical impact-evaluation studies finds that causal ML algorithms materially sharpen effect estimates relative to conventional semi-parametric specifications, particularly when covariate spaces are large and nonlinearities pervasive (Herman & Guo, 2023). More generally, reviews in the Swiss Journal of Economics and Statistics document how causal ML is being integrated into programme evaluation, labour-market studies and agricultural economics, often delivering more robust inference under weaker functional-form assumptions (Lechner, 2023).

Positioning our study within this emerging literature, we employ DML to re-estimate the core relationship between agricultural commercialization and women's empowerment. Doing so serves two purposes. First, it allows us to flexibly control for a rich set of household and farm variables without imposing arbitrary linearity or additivity restrictions. Second, by reporting both fixed-effects linear probability model estimates (our baseline) and their DML counterparts, we provide a robustness check that speaks directly to concerns about model misspecification and high-dimensional confounding. In short, the ML component of the paper is not a tangential add-on; it is an additional test of our main hypotheses and a contribution to the growing field of causal econometrics that blends identification strategies drawn from economics with the representational power of modern algorithms.

1.4. Paper Structure

The remainder of this paper is organized as follows: Section II reviews the relevant literature on gender dynamics in agricultural commercialization, highlighting the gap between qualitative insights and quantitative evidence. Section III outlines our theoretical framework, explaining the mechanisms through which commercialization might influence various dimensions of women's empowerment. Section IV describes our data sources and presents descriptive statistics on empowerment indicators and commercialization metrics across countries and over time. Section V details our regression results, followed by a discussion of findings in Section VI. Finally, Section VII concludes with policy implications and suggestions for future research.

II. WOMEN'S EMPOWERMENT AND CASH CROP COMMERCIALIZATION: A LITERATURE REVIEW

Agricultural commercialization is often associated with shifts in gender power dynamics, frequently to the detriment of women's empowerment. Fischer and Qaim (2012) note that as farming becomes more market-oriented, women tend to lose decision-making control because high-value "cash crops" are usually defined as male domains. This loss of control, in turn, has a marginal negative effect on nutrition. In many Sub-Saharan African contexts, men have historically managed lucrative export or cash crops while women focused on subsistence food farming, a pattern that commercialization reinforces (von Braun & Webb, 1989; Doss, 2001, as cited in Fischer & Qaim, 2012). For example, in Kenya, bananas were traditionally a women's crop, but the formation of producer groups to market bananas led to increased male control over banana income, with women's influence correspondingly reduced (Fischer & Qaim, 2012).

Qualitative case studies from across Africa provide concrete examples of women's disempowerment amid cash-crop transitions. In West Africa, The Gambia's rice commercialization offers a cautionary tale. Carney (1992) documented that an irrigated rice development project there reallocated women's traditional rice fields to male management, undermining women's customary land rights and reducing them to laborers on plots they once controlled. Women's access to the benefits of rice production became increasingly tenuous despite higher yields, as male household heads claimed the improved land and its output. In East Africa's high-value horticulture sector, Dolan (2002) found a similar dynamic in Kenya: when horticulture farming for export became lucrative under contract farming, men monopolized the contracts and earnings, while women (who supplied much of the labor) saw their decision-making and financial shares diminish. This shift provoked household tensions – in some cases, women resorted to social resistance (e.g. witchcraft accusations) to challenge husbands who withheld income. These ethnographic accounts from The Gambia and Kenya highlight how moving into commercial "male" crops can erode women's agency, even in domains where they previously had authority.

Recent quantitative studies continue to emphasize the unintended consequences of cash-crop adoption on gender equality, including examples from other regions of Africa and beyond. In Uganda, Ntakyo and van den Berg (2022) evaluated a government program promoting rice as a new cash crop and found it had a significant negative effect on women's empowerment in the household – women's input in farm decisions and control over income fell notably in villages that commercialized, even as men's decision-making power increased. Likewise, in Ethiopia, lentils have traditionally been considered a "women's crop," yet a qualitative study by Baada et al. (2023) revealed that with greater market integration, women became marginalized in the sale and use of lentil output, effectively losing out on the profits of a crop they largely cultivate. Similar patterns are reported in parts of South Asia, where commercialization of food crops often shifts control to men unless deliberate measures counteract prevailing gender norms (Quisumbing et al., 2015). Overall, the literature suggests that without gender-sensitive safeguards, the shift to high-value commercial agriculture can inadvertently reduce women's empowerment at both household and community levels, even as it boosts household incomes.

Even though gendered dynamics in agrifood systems among smallholders has been heavily studied in the past decades, quantitative studies showing the association between crop commercialization are severely lacking, more so when talking about non-staple sales. And among the existing studies explicitly addressing crop commercialization, they focus only on a single specific value chain, and are limited to specific regions or districts within a single country.

The following sections outline existing studies which talk about high-value cash crops and women's empowerment over our four studied domains (productive and income decisions, time allocation and ownership of assets), highlighting the lack of empirical quantitative studies explicitly addressing the relationships between cash crop commercialization and women's empowerment.

2.1. Composite Empowerment Indices

Composite indices provide an overall measure of women's empowerment by aggregating multiple dimensions such as decision-making, resource access, leadership, and time allocation. One prominent example is the Women's Empowerment in Agriculture Index (WEAI), which captures these facets in a single score. Studies using such composite indices find that greater overall empowerment of women correlates with positive household outcomes. For instance, in Bangladesh higher WEAI scores were significantly associated with increased household caloric intake and dietary diversity (Sraboni et al., 2014). In Sub-Saharan Africa and Asia, multi-country cross-sectional analyses similarly report that women's aggregate empowerment is linked to more diversified and resilient farm production (Connors et al., 2023). These findings suggest that when women achieve broad-based empowerment, including through engagement in cash cropping, their households often benefit in terms of income and food security (Sraboni et al., 2014; De Pinto et al., 2020).

Uwineza et al. (2021) conducted a multi-stage sampling study of 252 households in Rwanda's Northern Province and found that women's empowerment in agriculture positively and significantly influenced household farm commercialization. Their research revealed that a one-unit increase in women's empowerment score increased household farm commercialization by 2.53 units. Similarly, Olayide et al. (2021) examined cassava "seedpreneurship" in Nigeria using a sample of 901 respondents across four states and discovered that village seed entrepreneurship significantly enhanced women's empowerment. These studies collectively demonstrate that empowering women in agricultural systems can create a virtuous cycle, where increased decision-making authority and resource access lead to greater commercialization, which in turn further strengthens women's economic position and household welfare (Uwineza et al., 2021; Olayide et al., 2021).

Jeckoniah et al. (2022) use cross-sectional data from the Singida region in Tanzania and employ an econometric model where the dependent variable is an empowerment score based on decision-making, ownership of assets, decisions regarding nutrition and income use, and test two main regressors in separate models, one being high value cash-crop commercialization and the other sunflower commercialization. They only find a positive but weak (p < 0.1) association between selling high value cash crops and their empowerment score.

2.2. Decision-Making in Production

One key empowerment metric is women's decision-making power in agricultural production – for example, choices about which crops to plant or how to use inputs. Empirical research in SSA often finds that men dominate these production decisions in cash-cropping households. In Malawi, Mgalamadzi et al. (2024) observed that male heads of household typically decide what is grown on each plot, even when women contribute substantial labor. This dynamic can be exacerbated when farming shifts toward cash crops traditionally seen as "men's domain." In Uganda, a quasi-experimental study by Ntakyo & Berg (2022) on rice commercialization found that the program significantly reduced women's decision-making authority in production, while increasing men's control over crop choices. Similarly, case studies in West Africa show that once a crop becomes lucrative, men tend to take over its cultivation – for instance, crops like cassava and cocoyam in Ghana switched from predominantly female-managed to male-managed when they turned into cash earners (Baada et al., 2023). Quantitative analyses (e.g. double-robust regressions in Uganda) confirm that without safeguards, cash-crop programs can unintentionally marginalize women's voice in production decisions. Conversely, interventions that explicitly involve women – such as self-help groups in India – have been shown to increase women's say in farming decisions (Raghunathan et al., 2019). Overall, decision-making in production emerges as a critical indicator: greater female involvement in crop-related decisions is often used as evidence of empowerment, and its absence signals persistent gender gaps in commercialization processes.

2.3. Control over Income Use

Control over the use of agricultural income is another vital dimension of women's empowerment. This metric assesses whether women can influence or decide how proceeds from crops (especially cash crops) are spent. Research consistently demonstrates that men often control the bulk of income from cash cropping, which can limit the benefits women receive from their labor (Ambler et al., 2018). For example, in a study of smallholders in Central Malawi, even when women participated in market sales, men typically managed the cash and decided on expenditures (Mgalamadzi et al., 2024). The implications of this imbalance are significant: women's lack of income control can dampen their incentives to engage in cash crops and may lead to household spending patterns that prioritize less nutritious or less family-oriented purchases. A Uganda study by Ntakyo and van den Berg (2022) found a commercialization program had a negative impact on women's control over crop income, even as it increased men's financial decision-making power. Conversely, when women do control income, evidence suggests they allocate more resources to food, health, and education. In South Asia, increases in women's income share were linked to higher household calorie intake (Aromolaran, 2009) and in Ghana, women's control of farm income was associated with improved child nutrition. Econometric analyses in these studies (such as instrumental variable and panel regressions) reinforce a causal interpretation: empowering women in income decisions can enhance family welfare. Thus, the degree of women's say in cash-crop earnings is a telling empowerment indicator, with numerous studies showing that greater control by women leads to more equitable and welfare-improving outcomes.

2.4. Access to Land and Productive Resources

Access to and control over productive resources – especially land, but also credit, inputs, and extension services – is a fundamental component of women's empowerment in agricultural contexts. Many quantitative studies highlight that women in SSA have significantly less access to land ownership and farm inputs compared to men, which in turn affects their role in cash crop production (Doss et al., 2020; Kilic et al., 2015). For instance, a World Bank survey-based study in Malawi found a persistent gender gap in landholding size and fertilizer use, contributing to lower commercialization capacity for female farmers (Kilic et al., 2015). Without secure land rights or credit, women often focus on subsistence or low-value crops, leaving lucrative cash crops to men. This dynamic is illustrated in Kenya's high-value horticulture sector: Oduol et al. (2017) argue that women's participation in lucrative commodity chains was constrained by limited land and capital, even though targeted strategies (like tailored financial products in female-headed households) helped close some gaps. Econometric evidence from Kilic et al., 2015 pointed to resource endowments as significant predictors of a farmer's ability to engage in high-value cash cropping. In summary, access to productive resources is both a precondition and a metric of women's empowerment: studies with rigorous quantitative methods have found that enhancing women's land rights and input access can enable them to partake more equally in cash crop economies, thereby improving their bargaining power and status.

2.5. Time Allocation and Work Burdens

The allocation of time – particularly the burden of labor and unpaid work – is a critical yet sometimes overlooked aspect of women's empowerment in agriculture. In many SSA contexts, women shoulder a "triple role" encompassing farm work, domestic chores, and community responsibilities, leading to severe time poverty (Mgalamadzi et al., 2024). Quantitatively, time-use surveys and WEAI sub-indices on workload reveal that women involved in market-oriented agriculture frequently fail the empowerment threshold for the time domain, indicating excessive workloads (Alkire et al., 2013). In Ghana, Malapit and Quisumbing (2015) found that the time burden aspect of empowerment was inversely related to positive nutrition outcomes, suggesting that when women are overextended, the benefits of cash cropping on the family can be undermined. These findings are bolstered by econometric analyses showing a trade-off between women's farm labor and their leisure or rest time. As one study in Kenya's high-value export sector reported, women contract farmers earned more income but also worked significantly longer hours than men, leading to mixed feelings about empowerment (Maertens & Swinnen, 2009). Policy-oriented research emphasizes the need to reduce women's time burdens – for example, by providing labor-saving technologies or childcare support – as an integral part of women's economic empowerment in agriculture (Oxfam, 2017). Thus, time allocation is an essential metric: truly empowering women in cash crop economies requires not only increasing their access to resources and income, but also ensuring they are not overburdened by an unequal share of work.

2.6. Crop Diversification and Women's Empowerment

Women's empowerment and crop diversification are deeply intertwined in the agricultural literature. Studies from Bangladesh (De Pinto et al., 2020) and cross-country surveys in Burkina Faso, India, Malawi and Tanzania (Connors et al., 2023) show that when women have more decision-making power and participate in agricultural groups, households tend to diversify from staple cereals into fruits, vegetables and other nutrient-rich crops. These diversified portfolios not only improve dietary diversity and food security but also provide women with new income sources and opportunities to exercise agency, especially when market structures, such as Brazil's National School Feeding Programme, create demand for diverse produce and value women's labour (Valencia et al., 2021). Conversely, empowerment components like asset ownership have mixed effects, sometimes encouraging specialization in cereals or cash crops, underscoring that empowerment is multi-dimensional and context-dependent.

Causal evidence remains scarce; one quasi-experimental study (Schling & Pazos, 2024) shows that granting women informal land rights in Peru significantly increases crop diversity and food security without immediately improving empowerment scores. This suggests that while resources can facilitate diversification, broader empowerment may require additional changes in intra-household dynamics and supportive policies. Overall, the literature indicates that crop diversification is both a product and a driver of women's empowerment: diversified farms enhance women's roles in decision-making and market engagement, thereby strengthening their bargaining power, while empowered women are better positioned to adopt diverse cropping strategies, improving resilience and nutritional outcomes.

2.7. Contribution and Literature Gap

As mentioned earlier, no academic paper has tried to establish either an association or causality between crop commercialization (focusing on non-staples) and women's empowerment using our specific measures. While some have tried the reverse scenario (association between empowerment and commercialization), none have addressed the case of higher value non-staple crops, beyond analyzing qualitative cases from specific value chains in one country and subareas. Our contribution therefore is showing results for five countries, with multiple years and a panel structure, to explicitly address the association between crop portfolio and women's empowerment using a multifaceted index.

A close read of the evidence base confirms a strong "staple bias." The handful of studies that treat women's empowerment as the *outcome* and commercialization as the key treatment almost always look at rice or mixed staple baskets. The flagship example is Ntakyo and van den Berg's (2022) rice-programme evaluation in Uganda, which finds sizeable losses in female decision-power when households intensify paddy sales. By contrast, econometric work on non-staple, high-value crops is almost absent: only Mosha, Jeckoniah, and Boniface (2022) model a sunflower-specific commercialization index—and even there the impact on women's agency is statistically weak— while other horticulture or vegetable cases are qualitative (e.g., Balayar & Mazur, 2022). Our multi-country panel analysis, which isolates the commercialization share of *non-staple* crops and deploys a full A-WEAI-style index, therefore breaks fresh ground by moving the focus beyond

staples and supplying a large-sample estimates of how high-value crop shifts reshape women's empowerment.

Regarding machine learning employment, only two studies explicitly apply modern machine-learning methods to women's-empowerment metrics, and both use ML solely for dimensionality reduction rather than causal estimation or prediction. Jayachandran, Biradavolu, and Cooper (2023) harness constrained LASSO and random forests to shrink a 63-item agency module to five questions, while Saha and Narayanan (2022) rely on supervised LASSO to condense the 33-indicator Women's Empowerment in Nutrition Index into a 20-item short form. No published work to date applies double-machine-learning, causal forests, or similar techniques to estimate treatment effects on WEAI, pro-WEAI, or related indices, leaving a clear methodological gap for future research.

III. DATA AND METHODOLOGY

Our analysis leverages longitudinal household survey data from five Sub-Saharan African countries through the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative. This World Bank-supported program provides exceptionally detailed agricultural information, household characteristics, and community-level variables that enable comprehensive examination of women's empowerment dimensions alongside commercialization patterns.

Data Sources and Panel Structure

The empirical foundation of this study consists of nationally representative panel surveys conducted across multiple waves between 2010 and 2020, as detailed below:

Table 1. Survey instrument, waves and panel type by country analyzed.

Country	Survey Instrument	Survey Periods	Panel Type
Ethiopia	Ethiopia Socioeconomic Survey (ESS)	2011, 2013, 2015	Unbalanced
Malawi	Integrated Household Panel Survey (IHPS)	2010, 2013, 2016, 2019	Unbalanced
Nigeria	General Household Survey (GHS-Panel)	2010, 2012, 2015, 2018	Unbalanced
Tanzania	Tanzania National Panel Survey (TZNPS)	2010, 2012, 2014, 2020	Unbalanced
Uganda	Uganda National Panel Survey (UNPS)	2010, 2012, 2014, 2016, 2020	Unbalanced

To maximize statistical power while maintaining methodological rigor, we employ an unbalanced panel approach. This strategy accommodates households that were surveyed in multiple (though not necessarily all) rounds, optimizing the information extracted from available data. During fixed-effects estimation, households appearing in only a single wave are automatically excluded as they contribute no information about within-household variation over time and would constitute singletons in the estimation procedure (following standard econometric practice as described by Correia 2015).

Variable Construction and Controls

Our regression specifications maintain consistency in control variables across models. At the household level, we include demographic characteristics such as the household head's age and gender, educational attainment (measured as mean years of schooling among working-age household members), dependency ratio, overall household size, and proportion of income derived from non-agricultural sources. Agricultural controls are limited to cultivated land area (both linear and quadratic terms) to capture scale effects without introducing endogeneity concerns. We deliberately exclude variables related to input intensity and crop selection decisions, as these factors likely represent mechanisms through which commercialization affects empowerment rather than confounding variables.

Country Classification by Development Stage

To facilitate cross-country comparison and identify patterns associated with economic development levels, we classify the five countries into three distinct income strata based on several macroeconomic indicators as shown in Table 2.

Table 2. Economic Classification of Sample Countries

Country	GDP per capita (US$, constant)		Agricultural Indicators		Development
	Recent 5-yr avg.	Survey period avg.	Agric. GDP share (%)	Agric. growth rate (%)	Stratum
Nigeria	2,449	2,529	23	2	Upper
Tanzania	1,050	912	25	3	Middle
Uganda	930	858	24	5	Middle
Ethiopia	836	649	36	5	Lower
Malawi	560	542	23	3	Lower

This stratification reveals significant variation in economic conditions across our sample. Nigeria represents the highest income level with per capita GDP exceeding $2,400, while Malawi's figure remains below $600. Ethiopia stands out with agriculture comprising over a third of its economy, substantially higher than the approximately one-quarter share observed in the other countries. The agricultural growth trajectories also differ notably, with Uganda and Ethiopia experiencing more robust sectoral expansion compared to Nigeria's modest growth. These economic distinctions provide an important analytical dimension, allowing us to examine whether the relationship between commercialization and women's empowerment varies systematically with overall economic development.

3.1. Methodology: Abbreviated Women's Empowerment in Agriculture Index (A-WEAI)

Overview of A-WEAI

The Abbreviated Women's Empowerment in Agriculture Index (A-WEAI) is a streamlined version of the original Women's Empowerment in Agriculture Index (WEAI). Developed to measure women's empowerment and inclusion in the agricultural sector, the A-WEAI provides a more concise tool for assessing the roles and extent of women's engagement in agriculture. The index is composed of two sub-indices: the Five Domains of Empowerment (5DE) and the Gender Parity Index (GPI) (IFPRI, 2012).

This study focuses on the 5DE sub-index, which accounts for 90% of the total A-WEAI score. The 5DE is calculated based on five dimensions of empowerment in agriculture, each represented by one or two indicators. Due to data limitations in the LSMS-ISA surveys, we have modified the original A-WEAI methodology to exclude the group membership indicator and adjust the weights of the remaining indicators accordingly.

Modified A-WEAI Dimensions and Indicators

Our modified version of the A-WEAI includes five indicators across four dimensions:

Production focuses on input in productive decisions, carrying a weight of 1/4, reflecting a woman's voice in farming choices and non-farm enterprise activities. Resources consists of two components: ownership of assets (weighted at 1/6), which examines whether women control important resources like land and equipment; and access to and decisions on credit (weighted at 1/12), which measures their ability to obtain and manage loans and financial services. Income centers on control over the use of income, with a weight of 1/4, assessing women's authority in determining how household earnings are spent. Time examines workload, weighted at 1/4, which considers women and young girls who are "time poor" as per Bardasi & Wodon (2006) (See Appendix, Table A, for greater detail on the indicators). The group membership indicator, originally part of the Leadership dimension, has been omitted due to the lack of relevant data in the LSMS-ISA surveys. To maintain the overall structure of the index, we have redistributed the weight of this indicator equally among the remaining four dimensions.

Calculation of the 5DE Score

To calculate the 5DE score for each household, the process begins by determining whether any women in the household have achieved adequacy in each indicator based on specific criteria (which will be detailed separately). A value of 1 is assigned when a woman has achieved adequacy in an indicator, while 0 is assigned when adequacy has not been reached. These values are then combined into a weighted sum using the modified weights previously outlined. The final 5DE score is a bounded [0,1] index constructed from weighted indicator adequacy; we then apply the 0.75 empowerment threshold, with higher scores representing greater levels of empowerment. It's important to note that this resulting variable is not continuous in nature.

Empowerment Classification

After calculating the 5DE score, households are classified as empowered or disempowered:

- Empowered: 5DE score ≥ 0.75
- Disempowered: 5DE score < 0.75

This classification allows for the calculation of the headcount ratio of empowered households in the sample. The threshold indicates adequacy in at least 3 of the dimensions.

Limitations and Adaptations

The modification of the A-WEAI methodology, particularly the omission of the group membership indicator, may affect the comparability of our results with other studies using the standard A-WEAI. However, this adaptation was necessary due to data constraints in the LSMS-ISA surveys.

Furthermore, the specific questions and variables used to assess each indicator may vary slightly from the standard A-WEAI questionnaire, as we are working with existing LSMS-ISA data. These adaptations were made to best approximate the A-WEAI indicators given the available data.

3.2. Country-Specific Adaptations

This study utilizes data from the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) for five countries: Ethiopia, Malawi, Nigeria, Tanzania, and Uganda, which include a panel structure allowing for fixed effects regressions. For each country, we identified questions and variables that best approximate the A-WEAI indicators given the available data. It's important to note that the specific questions and their wording may vary across countries due to differences in survey design and local contexts.

Before analyzing the data, we first verify that the reported member IDs match those of female members in the household. We then capture whether at least one woman in the household has reported empowerment in each of the five indicators. The following table summarizes the key questions or variables used for each indicator across the six countries. We consider a household adequate in each dimension if a woman's member ID matches with any of these questions in each pillar.

Limitations and Considerations

The variations in survey questions and data availability across countries present challenges for perfect comparability. We have made our best efforts to select variables that most closely align with the A-WEAI indicators, but some approximations were necessary.

Despite these limitations, this adapted methodology allows for a valuable cross-country comparison of women's empowerment in agriculture, leveraging the rich data available in the LSMS-ISA surveys.

Assumptions and Considerations

In applying these questions to construct our adapted A-WEAI, we made several key assumptions:

For the workload indicator, we consider women over and under 15 years of age who work less than 50 and 9 hours per week, respectively, to have achieved adequacy (if not, they are "time poor" as per Bardasi & Wodon (2006)). This is an adaptation of the original A-WEAI threshold of 10.5 hours per day to better fit the weekly data available in most LSMS-ISA surveys.

In cases where multiple household members are involved in decision-making, we consider a woman to have adequate achievement if she is listed as one of the decision-makers (sole or joint decision-making, which is acceptable by IFPRI).

In most cases, we can see which member owns land, livestock and/or household assets. In Malawi, Tanzania and Uganda, we do not have information on ownership of household assets and, in Nigeria, all but livestock.

These assumptions allow us to create a consistent framework for assessing women's empowerment across the six countries, despite some variations in the available data. However, it's important to note that these adaptations may impact the comparability of our results with studies using the standard A-WEAI methodology.

Comparison of results with previous studies

Our results align closely with previously conducted findings regarding the WEAI methodology. A pilot survey conducted in 2014 in rural Uganda by IFPRI concluded that 59.72% of households are empowered (Malapit, H. et al, 2020). Our estimate is 59.62% in rural areas for 2014.

A 2017 study in Southern Nigeria (states of Ogun, Osun and Oyo) concludes that 72% of rural households are empowered (Adeyeye, O. et al. 2018). Our estimates for these states and rural households in 2018 is 70%.

A study of rural households in Malawi 2012 across 7 districts (Balaka, Dedza, Lilongwe, Machinga, Mangochi, Mchinji, and Ntcheu) show that 52% of households are empowered. Our estimate for 2013 (despite non-representativeness of districts) and rural households for those districts is 53%.

In Ethiopia, early 2017, a survey was conducted for a program evaluation. 57% rural households

from the control group had achieved empowerment in Oromia and Afar (Quisumbing, A, et al., 2022). Our estimates for 2015 for these regions and rural households are 56%, and 61% for 2018.

The difference arises with Tanzania, where a study conducted by Omondi, I. et al. (2021) found that, in Tanzania 2017, in the Mbeya, Njombe and Iringa districts, 43% of women surveyed were empowered. Our estimates, based on the available data, show this value to be 53% and 60% in 2014 and 2020, respectively. However, the Njombe district is not found in the LSMS-ISA, as it separated from Iringa district in 2012, and data at this level is not representative in our databases.

3.3 Econometric Model and Mathematical Motivation

To empirically examine the relationship between agricultural commercialization and women's empowerment, we employ a panel fixed-effects model that accounts for both the direct effect of commercialization and its interaction with the composition of crop sales. Our baseline specification (1) and marginal-effect derivative (2) are formulated as follows:

$$(1)\ E_{it} = \alpha_i + \gamma_t + \beta_1 C_{it} + X_{it}'\delta + \varepsilon_{it}$$

$$(2)\ E_{it} = \alpha_i + \gamma_t + \beta_1 C_{it} + \beta_2(C_{it} \times NS_{it}) + X_{it}'\delta + \varepsilon_{it}$$

where E_{it} represents the empowerment status of household i in time period t, measured as a binary indicator equal to 1 if the household is classified as empowered according to our modified A-WEAI framework, and 0 otherwise. C_{it} denotes the commercialization index, calculated as the ratio of agricultural output sold to total agricultural output produced in value terms. NS_{it} represents the non-staple share, defined as the proportion of sales derived from non-staple crops relative to total crop sales. The household-specific fixed effect α_i controls for time-invariant unobserved heterogeneity at the household level, while γ_t captures time-specific effects common to all households. X_{it} *is a vector of* time-varying control variables, and ε_{it} is the idiosyncratic error term.

The marginal effect of commercialization on empowerment can be derived by taking the partial derivative of the empowerment function (2) with respect to commercialization:

$$(3)\ \frac{\partial C_{it}}{\partial E_{it}} = \beta_1 + \beta_2 NS_{it}$$

This expression reveals that the impact of commercialization on women's empowerment is conditional on the composition of crop sales.

However, when we introduce the interaction term in (2), $(C_{it} \times NS_{it})$ essentially becomes $\frac{Non-staple\ sales_{it}}{Production_{it}}$, and, after rearranging $\beta_1 C_{it} + \beta_2(C_{it} \times NS_{it})$ in (2), we end up with:

$$(4)\ \beta_1\left(\frac{Staple\ sales_{it}}{Production_{it}}\right) + (\beta_1 + \beta_2)\left(\frac{Non-staple\ sales_{it}}{Production_{it}}\right)$$

When households engage exclusively in staple crop commercialization $NS_{it} = 0$, the marginal effect reduces to β_1, representing the baseline effect of staple crop commercialization on empowerment. As the proportion of non-staple crops in total sales increases, this effect is moderated by β_2. So, in essence, when we introduce the interaction term in (2), we observe how the crop shift from staples to non-staples associates with women's empowerment.

Based on the qualitative literature documenting gendered crop domains in Sub-Saharan Africa (Dolan, 2002; Fischer & Qaim, 2012; Ntakyo & van den Berg, 2022), we hypothesize that $\beta_1 > 0$ and $\beta_2 < 0$. This would indicate that while commercialization generally enhances women's empowerment, this positive effect diminishes or potentially reverses as sales shift toward non-staple crops that are traditionally male-dominated. The magnitude of β_2 relative to β_1 determines whether there exists a threshold of non-staple crop share beyond which the empowerment benefits of commercialization are completely negated.

The benefit of employing this interaction term approach lies in its ability to circumvent sample restriction issues that would otherwise limit our analysis. By interacting commercialization with the non-staple share, we avoid constraining our sample exclusively to households that engage in market activities. If we had instead used the share of non-staples in total sales as a standalone variable, households with zero sales would be necessarily excluded since this share remains undefined when total sales are zero. Similarly, using the share of non-staple sales in non-staple production would restrict our sample to only those households that cultivate non-staple crops, introducing potential selection bias. Our interaction approach resolves these methodological challenges because when a household does not participate in markets ($C_{it} = 0$), the interaction term ($C_{it} \times NS_{it}$) automatically equals zero regardless of what the non-staple share might theoretically be. This allows us to retain all households in our estimation sample—including non-sellers, exclusive staple crop sellers, and those commercializing both staple and non-staple crops—thereby enabling a more comprehensive examination of the relationship between agricultural commercialization patterns and women's empowerment across the full spectrum of household market engagement.

Control variables across all specifications include: natural logarithm of off-farm income (plus one), household size, dependency ratio, cultivated area (ha) and its squared term, logarithm of production (kg), binary for household experienced any shock in the past 12 months, consumption expenditure quintile, age and gender of the head of the household, and average years of education of the household members of working age, with time and household fixed effects when appropriate.

3.3.1 Non-linear specification and Random Forests

In order to explore non-linearity, we create four categorical bins based on the share of non-staples in total sales: staple-only (Q1), non-staple share of sales in the bottom quartile (Q2), share of non-staple in sales between 25th and 75th percentile (Q3), and non-staple specialized with a share of non-staples at the top quartile (Q4). The FE regression is then run based on equation (5).

$$(5) \; E_{it} = \alpha_i + \gamma_t + X_{it}'\delta + \sum_{k=1}^{4} \theta_k (C_{it} \cdot 1\{B_{it} = k\}) + \varepsilon_{it}$$

Regarding the DML specification, We estimate the nuisance functions in the DML step with Random Forests using grouped 5-fold cross-fitting at the household level: in each dataset we fit 15 forests (one for the outcome $g(X)$ and one for each treatment component $m_1(X)$ for C_{it} and for $m_2(X)$ for $C_{it} \times NS_{it}$. Each forest uses 600 trees, shallow depth and a minimum of 10 observations per leaf, with full parallelization and a fixed seed to stabilize out-of-fold predictions while limiting overfitting. Out-of-fold predictions are used to orthogonalize Y and D (commercialization share and interaction with non-staple sales share); we then run OLS on the residualized variables with household-clustered standard errors. The same procedure is repeated for the lag and lead placebo simples.

IV. DESCRIPTIVE STATISTICS

4.1. Empowerment Metrics Over Time

Cross-sectional patterns (Table 3) point to divergent trajectories: Uganda sustains high empowerment (>77 %) across waves, Malawi rises steadily to 70 %, while Tanzania, Ethiopia, and Nigeria display pronounced volatility. These differences suggest country-specific institutional or shock-related drivers rather than a uniform regional trend.

Panel results highlight instability. Outside Uganda—where 58 % of households are always empowered—most panel households cycle in and out of empowerment (Table 4). Within these "mixed" groups (Table 5), only 13–30 % secure lasting gains, whereas 63–71 % continue to fluctuate, and up to 20 % become disempowered. Thus, empowerment gains are rarely linear; policies must therefore focus not only on achieving empowerment but on safeguarding it over time.

Table 3. Producer households empowered across survey waves (%)

Country	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Ethiopia	-	44%	44%	55%	-
Malawi	40%	58%	62%	70%	-
Tanzania	-	69%	39%	58%	48%
Uganda	82%	77%	79%	85%	90%
Nigeria	-	57%	65%	70%	-

Table 4. Panel households who were always empowered, never empowered, and fluctuating between survey waves (%).

Country	Households Present in all Waves	Always Empowered (%)	Never Empowered (%)	Mixed (%)
Malawi	1018	15	6	79
Tanzania	1018	15	11	74
Uganda	888	58	2	40
Nigeria	795	30	13	57

Note: Malawi and Nigeria have three rounds of data, while Tanzania and Uganda have four. Ethiopia is omitted given the availability of only two waves, which doesn't permit this analysis.

Table 5. "Mixed" Panel households who became empowered, disempowered, and fluctuated between survey waves (%).

Country	Mixed Households	Became Empowered (%)	Disempowered (%)	Fluctuating (%)
Malawi	803	30	5	65
Tanzania	755	13	20	67
Uganda	355	15	17	68
Nigeria	612	25	6	69

Note: Malawi and Nigeria have three rounds of data, while Tanzania and Uganda have four. Ethiopia is omitted given the availability of only two waves, which doesn't permit this analysis.

4.2. Key variables by empowerment status

Appendix Table A2 summarizes mean differences between disempowered and empowered households in the two low-income countries—Ethiopia and Malawi. A clear pattern emerges: empowerment is systematically associated with stronger market engagement and better human capital. Empowered households exhibit a significantly higher commercialization index (0.18 vs. 0.15 in Ethiopia; 0.14 vs. 0.09 in Malawi) and purchase a larger share of their food in Ethiopia, suggesting deeper integration into output and consumption markets. They also command higher average years of education (+0.49 years in Ethiopia; +0.79 years in Malawi) and smaller dependency ratios, while being noticeably less likely to be male-headed. Meso-level advantages

are equally pronounced: empowered households in both countries live in areas with denser road networks (+0.85 km/km² in Ethiopia and +4.70 km/km² in Malawi), reflecting better physical connectivity. Notably, the poverty headcount is significantly lower for empowered households only in Malawi (43 percent vs. 32 percent).

Appendix Table A3 contrasts the middle- and higher-income group (Tanzania, Uganda, Nigeria). Across these countries, empowerment remains linked to commercial orientation but the ancillary correlates are more heterogeneous. In Tanzania and Nigeria, empowered households score markedly higher on the commercialization index (+0.08 and +0.05, respectively) and cultivate larger landholdings—traits typical of commercial smallholders. Uganda diverges: the empowered group shows a marginally *lower* commercialization score and a higher share of off-farm income. Interestingly, road density works in opposite directions: empowered households in Tanzania reside in *less* connected areas, whereas the opposite holds in Nigeria. Education differences persist (up to +1.06 years in Nigeria), but the sign on the dependency ratio flips across countries. Poverty differences also vary: empowerment coincides with lower poverty in Nigeria but higher poverty in Uganda, reminding us that the Women's Empowerment in Agriculture Index (A-WEAI) captures agency rather than welfare per se.

4.3. Results by dimension of empowerment

Appendix Table A4 provides dimensional empowerment rates for the most recent survey wave. Decision-making over production and workload autonomy are the dimensions most frequently achieved, exceeding 80 percent in all countries. By contrast, credit access remains the weakest link, with empowerment rates languishing below 25 percent everywhere except Nigeria (62 percent). Asset ownership is high (≥ 86 percent) in four of five countries.

V. RESULTS

5.1 Women Do Have Input in Income Usage from Cash Crop Sales

Surprisingly, data from the LSMS-ISA in our five countries tell a different story than the qualitative research: women do actually have control over income use derived from high-value crop sales. The conventional wisdom suggests that households who sell cash crops have barely any women deciding over income use, as commercialization supposedly leads to male capture of agricultural proceeds. However, we classified oilseeds, horticultural fruits and vegetables, and non-food industrial crops as cash crops and found evidence that contradicts this narrative. As shown in Table 6, In Ethiopia, 2018, 41% of selling households who harvested cash crops had women deciding over the use of their income from sales, and 44% for the income derived from staple crop sales. Even among producers who only harvested staple crops, 34% had women in the household deciding over use of sales income.

Our longitudinal analysis reveals even more striking patterns. Across most countries, women's decision-making power over cash crop income is not only present but actually increasing over time. In households that harvested and sold both cash and staple crops, women's control over cash crop income rose from 55.9% to 76.9% in Malawi, from 50.7% to 58.3% in Tanzania, and from 59.1% to 69.4% in Uganda. These levels of female decision-making—ranging from 40% to 77%—directly contradict the assumption that cash crop commercialization inevitably marginalizes women from income control.

These changes are not merely descriptive trends. Statistical analysis using two-proportion z-tests reveals that most improvements in women's decision-making power are statistically significant ($p < 0.05$). For cash crop income decisions, Malawi showed a 21.0 percentage point increase ($z = 8.53$), Tanzania increased by 7.6 percentage points ($z = 2.81$), and Uganda by 10.3 percentage points ($z = 4.27$). The strength of these effects indicates real changes in household dynamics rather than sampling variation. Even more, women's control over staple crop income in staple-only households showed remarkable improvements, with Uganda increasing by 58.1 percentage points ($z = 10.15$) and Malawi by 38.9 percentage points ($z = 7.60$).

Contrary to the narrative that cash crop commercialization disempowers women, our data suggest that women maintain substantial decision-making power in households engaged in cash crop sales. By the last wave, women in cash crop-selling households decided over income use in 40.6% of cases in Ethiopia, 76.9% in Malawi, 58.3% in Tanzania, and 69.4% in Uganda. These rates are comparable to or even exceed those in staple-only households in some countries, challenging the assumption that crop commercialization necessarily leads to male domination of agricultural income.

These findings have important implications for agricultural development policy. Rather than avoiding cash crop promotion due to fears of disempowering women, our evidence suggests that women can and do maintain control over income from commercial agriculture in many contexts. The high and increasing rates of women's decision-making power over cash crop income—reaching over 75% in Malawi and nearly 70% in Uganda—demonstrate that agricultural

commercialization and women's empowerment are not mutually exclusive goals. However, the heterogeneity across countries indicates that supportive policies and institutions may be necessary to ensure women's inclusion in commercial agriculture benefits.

Table 6: Change in Women's Decision-Making Power (First Wave to Last Wave): Percentage of households that have women who decide on income use from crop sales. Descriptive statistics only.

Household Type	Harvested and Sold Cash and Staple Crops	Harvested and Sold Cash and Staple Crops	Harvested and Sold Only Staples
Country	Decision over Cash Crop Income Use	Decision over Staple Crop Income Use	Decision over Staple Crop Income Use
Ethiopia (2012-2018)	37.7% → 40.6% (+2.9pp)	41.9% → 44.4% (+2.5pp)	35.4% → 33.6% (-1.8pp)
Malawi (2010-2019)	55.9% → 76.9% (+21.0pp)*	25.0% → 40.0% (+15.0pp)*	43.7% → 82.6% (+38.9pp)*
Tanzania (2012-2020)	50.7% → 58.3% (+7.6pp)*	36.5% → 37.3% (+0.8pp)	44.0% → 41.2% (-2.8pp)
Uganda (2012-2020)	59.1% → 69.4% (+10.3pp)*	57.4% → 78.6% (+21.2pp)*	29.8% → 87.9% (+58.1pp)*
Nigeria (2012-2018)	38.4% → 32.7% (-5.7pp)*	24.3% → 27.8% (+3.5pp)*	38.0% → 50.7% (+12.7pp)*

Note: (*) denotes statistically significant change over time.

5.1. Initial Model: Empowerment on Overall Crop Commercialization

We begin with a simple two-way fixed effects linear probability model that only examines the association of the ratio of sales in total production (value terms) and empowerment status. We choose LPM over logistic regression given the convenience of interpretability, as estimators have been proven to be reliable under LPM when the dependent variable is not a rare event (on average, more than half of our samples are empowered).

As we can observe, a one-unit increase (going from 0 sales to 1 (selling all production)) in the commercialization index has a strong positive association with empowerment, predicting as much as a 36% pp increase in the likelihood of being empowered in Ethiopia, with null correlation in Nigeria and even negative (but negligible) in Uganda.

Table 7: Model without Interaction (Model 1). Two-way fixed effects model: Empowerment on share of crops commercialized (value terms) and household, farm controls.

Income Stratum	Low	Low	Middle	Middle	High
	Malawi	Ethiopia	Uganda	Tanzania	Nigeria
Commercialization index	**0.29***	**0.36***	**-0.04****	**0.18***	0.04
	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)
Constant	**0.72***	0.17	**0.83***	**0.76***	**0.66***
	(0.07)	(0.13)	(0.05)	(0.05)	(0.20)
Household controls	Yes	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes	Yes
Observations	5,976	6,435	6,889	7,569	5,013
R-squared	0.43	0.55	0.47	0.51	0.60

5.2. Main Model A: Introducing Share of Non-Staples

Afterwards, we expand the model by adding the interaction term with the share of non-staples in sales, which reveals negative correlations in Malawi, Ethiopia and Tanzania.

Table 8: Model with Interaction (Model 2). Two-way fixed effects model: Empowerment on share of crops commercialized (value terms), its interaction with share of non-staples in total sales, and household, farm controls.

	Malawi	Ethiopia	Uganda	Tanzania	Nigeria
Income Stratum	Low	Low	Middle	Middle	High
Commercialization Index	0.42***	0.68***	-0.05*	0.30***	0.02
	(0.06)	(0.08)	(0.07)	(0.03)	(0.04)
Commercialization Index × Non-Staples Share	-0.21***	-0.44***	0.02	-0.15***	0.05
	(0.07)	(0.08)	(0.03)	(0.04)	(0.06)
Log(Off-farm income + 1)	0.01***	0.01***	0.00***	-0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Consumption quintile	0.01**	-0.00	0.00	0.01	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Head age	-0.00**	0.01***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male head	-0.19***	-0.12	-0.12***	-0.31***	-0.30**
	(0.03)	(0.11)	(0.03)	(0.02)	(0.14)
Education of HH workforce	0.00	-0.00	-0.00	0.00*	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dependency ratio	0.01	-0.01	-0.01*	0.02*	0.00

	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Household size	**0.02***	-0.00	**0.01***	-0.00	**0.01***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Cultivated area (ha)	**0.06***	0.00	0.00	**0.02***	**-0.01***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Cultivated area squared	**-0.01***	0.00	-0.00	**-0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household experienced shocks	0.01	0.00	-0.01	**0.05****	-0.03
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Constant	**0.50***	0.13	**0.88***	**0.62***	**0.66***
	(0.06)	(0.12)	(0.05)	(0.05)	(0.20)
Observations	5,976	7,314	5,126	7,568	5,013
R-squared	0.44	0.56	0.68	0.51	0.69

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include household and time fixed effects with standard errors clustered at the household level.

5.3. Main Model B: Double Machine-Learning

Double/de-biased Machine Learning (Double ML) is a semi-parametric framework that combines high-capacity prediction algorithms with Neyman-orthogonal moment conditions to obtain $\sqrt{n}$-consistent causal estimates even when the number of controls is large and their effects highly non-linear. In the first step, machine-learning models such as random forests flexibly purge both the outcome and the treatment of their dependence on the control set, using cross-fitting to avoid own-observation bias. The residualised variables are then plugged into an orthogonal score that is mathematically insensitive to first-stage regularisation error, restoring unbiasedness and delivering asymptotically valid standard errors (Chernozhukov et al., 2018).

Following the double/de-biased machine-learning framework (Chernozhukov et al., 2018), estimation proceeds in two tightly linked stages. In the first stage, we fit high-capacity random-forest learners to the panel data in a cross-fitting scheme: one forest predicts each household's empowerment status (0/1) from the full set of controls (farm size, demographic composition, reported shocks, fixed effects, etc.), while a second forest predicts the commercialization index (C_{it}) and, separately, its interaction with the household's share of non-staples in total sales. These flexible, out-of-fold predictions purge both the outcome and the treatment variables of any systematic variation that can be explained by observable covariates, without imposing a priori functional-form restrictions. In the second stage, we regress the residualised empowerment outcomes on the residualised C_{it} and its interaction term using Neyman-orthogonal moment conditions; because the orthogonal score is insensitive to first-stage estimation error and each fold's residuals are computed on data unseen by its forests, the resulting coefficients remain √n-consistent and asymptotically normal despite the complexity of the nuisance functions. However, this does not rule out endogeneity caused by reverse causality, but provides highly robust correlations.

Table 9 reports the within-household estimates from the Double-ML partially-linear specification, where the commercialization index (C_{it}) enters as the main treatment and its interaction with the household's share of non-staples in total sales captures heterogeneity. In Malawi, Ethiopia and Tanzania, a one-unit increase in C_{it} is associated with empowerment gains of roughly 40, 73 and 24 percentage-points respectively, evaluated at zero non-staple sales; Nigeria registers a more modest but still significant 0.11 pp effect, whereas Uganda shows a very weak but positive association. Across the three countries with strong main effects, the interaction term is negative and significant, indicating that empowerment gains from commercialization shrink as households specialise in non-staple crops. For example, in Ethiopia an entirely non-staple-oriented household would experience an empowerment premium roughly half that of an otherwise similar household focused on staples. Nigeria is the lone exception: the interaction term there is positive, although only marginally significant at the 10 percent level, suggesting that diversification into non-staples may complement commercialization in that setting.

The omitted-variable-bias diagnostics in Table 5 corroborate the robustness of the main C_{it} coefficients in Malawi, Ethiopia and Tanzania. A hypothetical confounder would need to explain at least 10 to 15 percent of the residual variance in both women's empowerment and the commercialization index—over and above the rich set of controls and fixed effects—to bring those point estimates to zero, and slightly less to render them insignificant. Nigeria's main effect is somewhat more fragile (RV≈5 percent), while the Uganda estimates could be overturned by minimal hidden bias, mirroring their statistical insignificance. Interaction effects are uniformly less robust, with robustness values below seven percent in all panels, highlighting that the moderating role of non-staple specialisation should be interpreted cautiously and, where possible, probed with additional instruments or qualitative evidence.

Table 9. Double-ML estimates of empowerment on crop commercialization and its interaction with share of non-staples in total sales, household and farm controls, time and household fixed effects.

Country	β_1 (C_{it})	(SE)	95% CI β_1	β_2 ($C_{it} \times NS_{it}$)	(SE)	95% CI β_2
Malawi	0.42***	(0.06)	[0.31, 0.53]	−0.21***	(0.07)	[−0.36, −0.07]
Ethiopia	0.65***	(0.07)	[0.50, 0.79]	−0.45***	(0.08)	[−0.61, −0.28]
Uganda	-0.05*	(0.03)	[−0.1, -0.01]	0.02	(0.03)	[−0.05, 0.09]
Tanzania	0.30***	(0.03)	[0.23, 0.36]	−0.15***	(0.04)	[−0.23, −0.06]
Nigeria	0.03	(0.04)	[−0.04, 0.10]	0.04	(0.06)	[−0.08, 0.16]

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include household and time fixed effects with standard errors clustered at the household level. All controls included, alongside household and time fixed effects.

Table 10. Robustness values for hidden confounding

Country	RV β_1 (%)	RVa β_1 (%)	RV β_2 (%)	RVa β_2 (%)
Malawi	9.7	7.8	2.9	0.9
Ethiopia	14.6	12.6	6.4	4.3
Uganda	0.8	0.0	1.1	0.0
Tanzania	10.1	8.3	4.2	2.3
Nigeria	5.0	2.7	2.6	0.2

Note: RV is the percentage of residual variance in both outcome and treatment that an unobserved confounder would need to explain to drive the point estimate to zero; RVa performs the same calculation for the 95 percent confidence interval. All models absorb household and wave fixed effects and control for farmland characteristics, household demographics, log off-farm income and reported shocks, with flexible random-forest learners for nuisance functions and five-fold cross-fitting.

5.3.1 Placebo Tests for Reverse Causality or Persistent Factors

The forward-shift placebo—where the Commercialization Index and its non-staple interaction are replaced by future values from the next survey wave—offers a stringent pre-trend check (Feler &

Senses (2017); Irastorza-Fadrique et al. (2023)). Using the future $(t+1)$ value of the Commercialisation Index and interaction term as placebo in a double machine-learning regression with fixed effects helps rule out pre-existing empowerment trends: if women's empowerment were already on an upward trajectory *before* commercialisation intensifies, that latent trend would spuriously link today's empowerment to next year's C_{it+1} and $C_{it+1} \times NS_{it+1}$. A null lead coefficient therefore reassures that the baseline estimate is not simply capturing such underlying, non-causal momentum.

Using the updated two-sided placebos (lag and lead, Table 11), the level effect β_1 fails in Malawi, Ethiopia, Uganda and Tanzania—each shows a significantly negative mis-timed coefficient—implying women's empowerment co-moves with longer-run commercialization or anticipatory factors there; thus β_1 in these three panels should be treated as an upper bound absent stronger identification (e.g., valid external instruments). By contrast, Nigeria shows null placebos for β_1, supporting a cleaner level interpretation in those two cases. For Uganda, the lead placebo for β_1 is significant (fail), while β_2 is borderline pass; thus the level effect is fragile to pre-trend concerns. For the interaction β_2, the forward (lead) placebo is null in Malawi, Tanzania, and Nigeria (pass) and significant in Ethiopia (fail). On a two-sided basis, Malawi fails on the lag but passes the lead, Tanzania, and Nigeria pass both, and Ethiopia fails both. Overall, the two-sided placebo undermines causal claims for the average level effect in 3/5 panels, while lending credible support to a cash-crop-intensity gradient in Tanzania, Uganda, and Nigeria, with Malawi and Ethiopia failing.

Table 11. Placebo test results

Country	Placebo β_1 (C_{it})	p-value	Placebo β_2 ($C_{it} \times NS_{it}$)	p-value	Pass / Fail
Malawi	-0.25 *** (0.07)	< 0.01	0.20 ** (0.09)	0.033	**Fail (both)**
Ethiopia	-0.67 *** (0.09)	< 0.01	0.50 *** (0.10)	< 0.01	**Fail (both)**
Uganda	0.06 ** (0.03)	0.027	-0.05 (0.03)	0.093	Fail (β_1), Borderline Pass (β_2)
Tanzania	-0.14 *** (0.04)	< 0.01	0.01 (0.04)	0.864	Fail (β_1), Pass (β_2)
Nigeria	-0.02 (0.04)	0.670	-0.09 (0.06)	0.151	Pass (both)

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05. Having a significant coefficient means it failed the placebo test. Null hypothesis is no significant effect.

5.4. Breakdown by Empowerment Dimension

In this section we re-run the main regressions with the interaction term, separately by each empowerment dimension binary, alongside time and household fixed effects, and our set of controls. Complete results are shown in Table B1, Appendix.

The appendix (Table B1) shows that the Crop Commercialization Index (C_{it})—the share of total crop sales in production—has its clearest and most consistent association on women's decision-making over household income. In every country but Uganda, higher C_{it} translates into markedly higher probabilities that women help decide how different sources of income are used, with point estimates ranging from roughly twenty points in Nigeria to fourty five in Tanzania.

By contrast, the interaction term—which captures the proportion of marketed output coming from non-staple cash crops— often tempers or reverses the benefits of commercialization. For income decisions, the interaction coefficient is negative in Ethiopia and Tanzania, suggesting that an increasing tilt toward higher-value non-staples re-centralises control in men's hands or outside the household altogether. Nigeria, Uganda and Malawi stand out as an exception, with a near-zero interaction effect, hinting that differences in crop portfolios or marketing channels could moderate gendered trade-offs.

Across the remaining A-WEAI dimensions, crop commercialization shows vague associations. Ownership of assets sees a negative correlation in Nigeria when households couple high commercialization rates with a high share of non-staples in total sales, whereas in Tanzania this is positively correlated with women being responsible for credits acquired.

The coefficient plots in Figure 1 (main C_{it} effects) and Figure 2 (C_{it} × non-staple share) visualise these patterns at a glance. C_{it}'s income-empowerment gains are consistently positive and precisely estimated, whereas the blue bars for non-staple specialisation are frequently negative or wide, emphasising how crop mix conditions the gender dividends of commercial agriculture.

Figure 1. Empowerment Dimensions (1 = achievement in said dimension) on Crop Commercialization Index.
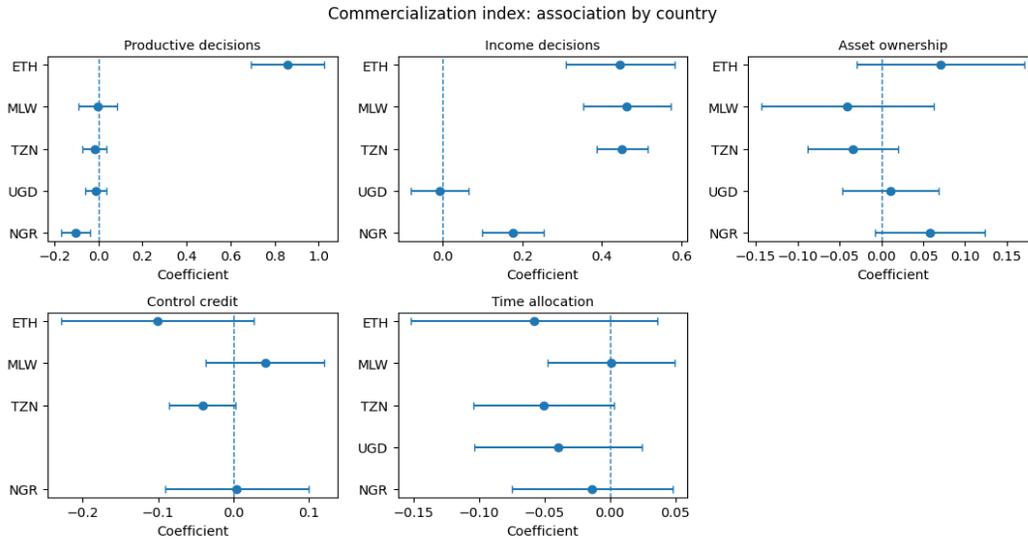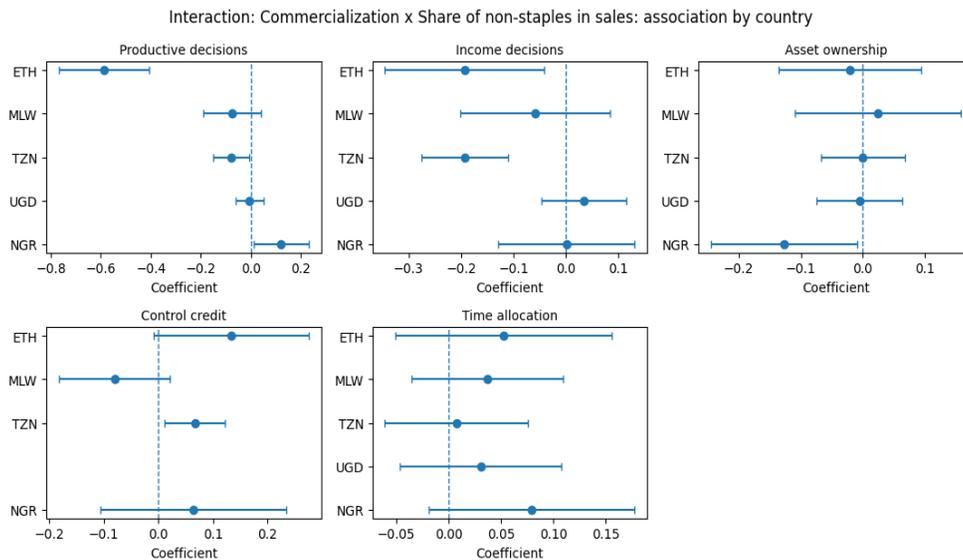

Figure 2. Empowerment Dimensions (1 = achievement in said dimension) on Share of non-staple sales in total production.

5.5 Quasi-Experimental Design: Propensity Score Matched Difference-in-Differences

To estimate the causal impact of agricultural commercialization, this study employs a propensity score matched difference-in-differences (PSM-DiD) approach. This quasi-experimental method is chosen to mitigate potential selection bias and account for unobserved heterogeneity inherent in observational panel data (Heckman et al., 1997).

The first stage of the analysis uses Propensity Score Matching (PSM) to address selection bias, which arises because households that choose to commercialize may be systematically different from those that do not. Following the framework developed by Rosenbaum and Rubin (1983), we estimate a household's probability (propensity score) of entering the market based on a rich set of pre-treatment observable characteristics, such as household demographics, farm size, crop production, and asset wealth. Each "treated" household—one that begins selling crops after the baseline period (binary variable of selling any amount of crops)—is then matched to an observably similar "control" household that remains as non-seller throughout the entire period span. This process creates a balanced sample that is statistically comparable at the baseline, strengthening the research design. Our analysis runs multiple matching algorithms (caliper, mahalanobis, nearest-neighbor, kernel, stratification and radius matching) and chooses the one that has the best balance between bias reduction and retention of observations. Afterwards, we run a second quasi-experiment among crop sellers, where the treatment is selling specifically high-value crops (binary variable).

The second stage applies a Difference-in-Differences (DiD) model to this matched sample. The DiD method estimates the treatment effect by comparing the change in outcomes for the treatment group (before vs. after commercializing) to the change for the matched control group over the same period (Ashenfelter & Card, 1985). A crucial identifying assumption for any DiD model is that of parallel trends. This assumption requires that, in the absence of treatment, the outcome variable for the treatment group would have followed the same trend as that of the control group (Angrist & Pischke, 2009).

The algorithm frequently selected nearest neighbor and mahalanobis matching, usually with 1 or 3 neighbors, and post-match diagnostics show mean standardized mean differences (SMDs) well below the standard 0.10 threshold (Table 12), which confirm that the subsequent DID estimates are built on a strong foundation of comparable groups, lending confidence to the causal interpretation of our findings.

The results shown in Table 12 reveal a clear and significant positive relationship between the decision to participate in crop selling and empowerment, although this effect varies by the type of crop commercialized and by country. The broadest measure, which captures the impact of moving from subsistence to selling any crops, showed a statistically significant and positive effect on empowerment in Malawi, Ethiopia, Tanzania (p<0.001) and Nigeria (p=0.02). Then, for the second quasi-experiment among crop sellers, where the treated are households that began selling cash crops (decision to add/switch to high-value crops in the sales portfolio), the analysis found a similar significant positive impact in Malawi (p=0.005), and Ethiopia (p<0.1). This suggests that

the initial entry into crop markets, and particularly cash crop markets, is a powerful driver of increased household empowerment. Notably, these effects were not statistically significant in Uganda for either measure.

Beyond the primary treatment effects, the regression models consistently highlight the importance of diversified income streams. Across nearly all countries and analyses, the logarithm of non-farm income was a strong and statistically significant positive predictor of empowerment.

While our PSM-DID estimates reveal substantial heterogeneity in empowerment effects across countries and commercialization pathways, important limitations constrain the causal interpretation of these findings. The parallel trends assumption, fundamental to DID identification, could only be partially tested due to limited panel waves—ranging from just two periods in Ethiopia, three in Nigeria, four in Malawi and Tanzania, and five in Uganda. This data structure severely restricts our ability to detect pre-treatment trends, with Ethiopia's large effect (42.9%) being particularly suspect given the impossibility of pre-trend testing with only two periods. Our placebo tests, which examine whether "effects" appear before actual treatment, provide some reassurance where implementable: Malawi and Nigeria are the most credible cases, which pass the pre-trend and placebo tests. For the case of Tanzania, while pre-trends pass, the placebo test fails for one cohort for each of the quasi-experiments. While Uganda fails the placebo test for entry to the markets, the association with empowerment is weak and barely significant, and fails one cohort for the first experiment. Ethiopia cannot rely on parallel trend tests as it only has two waves of data: baseline-difference placebos passes for entry to the market but fails for cash crop adoption in sales, so we do not rely on the latter. Full diagnostics are in Annex Table C1 and C2.

However, even these tests have limited power to detect subtle violations given the short panels. Nigeria and Uganda show intermediate reliability with three to five periods but smaller correlations with empowerment (and borderline null in Uganda). Given these constraints, our estimates should be interpreted as robust associations rather than definitive causal effects, with the Malawi and Tanzania commercialization results representing our most credible findings, Ethiopia's results requiring particular caution.

Table 12: PSM-DID Estimates of Agricultural Commercialization on Household Empowerment (Binary)

Country	Experiment Type (Binary Treatment Variable)	Coefficient (ATT)	P-val	Standard Error	N (Households)	Post-Matching Mean SMD
Malawi						
	Selling Crops	**0.286*****	<0.001	(0.048)	507	0.068
	Selling Cash Crops, Conditional on Selling	**0.141*****	0.005	(0.050)	468	0.077
Ethiopia						
	Selling Crops	**0.430*****	<0.001	(0.079)	531	0.066
	Selling Cash Crops, Conditional on Selling	**0.165***	0.097	(0.099)	550	0.068
Uganda						
	Selling Crops	**-0.08***	0.078	(0.046)	552	0.078
	Selling Cash Crops, Conditional on Selling	-0.05	0.176	(0.033)	660	0.053
Tanzania						
	Selling Crops	**0.258*****	<0.001	(0.057)	781	0.042
	Selling Cash Crops, Conditional on Selling	0.067	0.228	(0.055)	713	0.049
Nigeria						
	Selling Crops	**0.13****	0.02	(0.054)	1,086	0.039
	Selling Cash Crops, Conditional on Selling	0.06	0.17	(0.05)	915	0.030

Notes: The dependent variable is a binary indicator for household empowerment. The table displays the coefficient for the Average Treatment Effect on the Treated (ATT), which corresponds to the treat_post interaction term from the Difference-in-Differences (DID) model. Standard errors, reported in parentheses, are clustered at the household level. Significance levels are denoted as: *** p<0.01, ** p<0.05, * p<0.10.

We benchmarked a standard two-way fixed-effects DID (TWFE) against the staggered-adoption estimator of Callaway & Sant'Anna (2021). Across countries, the two approaches yield broadly consistent conclusions for both "sell any crop" and "sell cash crops among sellers" as shown in Table 13. Methodologically, for countries with more than 2 periods, the staggered adoption model should be a better fit, given that households may begin selling at different periods after being non-sellers at baseline. Ethiopia is excluded given the availability of only two periods, which does not have a staggered adoption. We also verified pre-trends with event-study leads (Table C3, Annex): Malawi, Tanzania, and Uganda do not reject joint pre-trend nulls; Nigeria lacks sufficient pre-periods to test formally, so we flag its results accordingly.

Table 13. Comparison of results from TWFE DID and Staggered Adoption DID (CSDID)

Experiment A. Selling any crop: TWFE vs CSDID

Country	TWFE DID: ATT (SE); p	CSDID: ATT (SE); p
Malawi	**0.237***** (0.037); <0.001	**0.313***** (0.056); <0.001
Tanzania	**0.272***** (0.041); <0.001	**0.161**** (0.068); 0.017
Uganda	**-0.068*** (0.037); 0.066	**-0.157***** (0.053); 0.003
Nigeria	**0.075**** (0.035); 0.033	0.085 (0.065); 0.193

Experiment B. Selling cash crops among sellers: TWFE vs CSDID

Country	TWFE DID: ATT (SE); p	CSDID: ATT (SE); p
Malawi	**0.134***** (0.033); <0.001	**0.144**** (0.066); 0.029
Tanzania	**0.061*** (0.037); 0.096	0.002 (0.084); 0.980
Uganda	**-0.068***** (0.026); 0.008	**-0.163***** (0.047); 0.001
Nigeria	**0.066**** (0.030); 0.025	0.008 (0.062); 0.899

5.6 Crop Diversification and Non-Linearity of Non-staple Share in Sales

One potential explanation as to the positive correlation when examining the extensive margin, but a negative association with share of non-staple sales in the intensive margin, could be that the effect of non-staple share in total sales is non-linear.

Hence, we run an additional analysis. Among sellers, given that we record the share of sales coming from non-staple crops, we classify households into four groups: those who sell only staples; those with a low non-staple share (bottom quartile among non-staple sellers); those with a moderate non-staple share (middle half); and those that are specialized in non-staples (top quartile). To study how production breadth matters, we split the sample into two halves—below- and above-average crop diversification (reverse Herfindahl Index based on quantity produced (kg) of different crops)—using survey weights. Empowerment is then related to commercialization within each of the four sales-mix groups, controlling for household fixed characteristics and common time shocks, with standard errors clustered by household.

Table 14. Non-linear effect of selling crops at different cash-crop sales portfolios.

Panel A: Below Average Diversification

Variable	Malawi	Ethiopia	Tanzania	Uganda	Nigeria
Commercialization index (Sells only staples)	**0.50*** (0.09)**	**0.69*** (0.14)**	**0.23*** (0.05)**	-0.07 (0.05)	0.015 (0.06)
Commercialization index (Low share of non-staples in sales)	0.25 (0.25)	0.38 (0.39)	**0.38*** (0.10)**	-0.09 (0.08)	0.05 (0.15)
Commercialization index (Medium share of non-staples)	**0.57** (0.21)**	**0.51*** (0.12)**	**0.22** (0.08)**	0.001 (0.05)	0.06 (0.10)
Commercialization index (Sells mostly non-staples)	**0.21* (0.11)**	**0.22*** (0.05)**	0.08 (0.05)	-0.04 (0.03)	0.09 (0.07)
Obs.	2,564	2,717	2,652	3,177	1,524
Within R²	0.05	0.07	0.09	0.01	0.03
Controls	Yes	Yes	Yes	Yes	Yes
Time and Household FE	Yes	Yes	Yes	Yes	Yes

Panel B: Above Average Diversification

Variable	Malawi	Ethiopia	Tanzania	Uganda	Nigeria
Commercialization index (Sells only staples)	**0.50*** (0.11)**	**0.71*** (0.18)**	**0.30*** (0.08)**	-0.05 (0.08)	**0.155** (0.08)**
Commercialization index (Low share of non-staples in sales)	**0.95*** (0.24)**	**0.90*** (0.19)**	**0.21** (0.10)**	-0.13 (0.08)	0.07 (0.15)
Commercialization index (Medium share of non-staples)	**0.55*** (0.13)**	**0.40*** (0.11)**	0.09 (0.07)	-0.057 (0.05)	**0.16** (0.07)**
Commercialization index (Sells mostly non-staples)	**0.19** (0.08)**	**0.30*** (0.08)**	0.10 (0.06)	-0.075 (0.05)	0.06 (0.10)
Obs.	2,238	2,930	2,866	3,177	1,916
Within R²	0.06	0.04	0.07	0.03	0.06
Controls	Yes	Yes	Yes	Yes	Yes
Time and Household FE	Yes	Yes	Yes	Yes	Yes

Notes: *Robust standard errors in parentheses (clustered at household id). Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Across countries, greater commercialization is generally associated with higher empowerment, and the relationship is stronger when households sell at least some non-staple products and when their production is more diversified. The pattern is clearest in Ethiopia and Malawi, and moderate in Tanzania. Interestingly, in Nigeria, only the production-diversified producers see a positive association with selling intensity, specifically in selling only staple crops (both) and a medium share of non-staples in the latter.

Another implication of the results is that, contrary to the conventional wisdom, even households (diversified or not) who mostly sell non-staple crops, still present a positive correlation between selling their production and women's empowerment. The similar coefficient among the groups (with specialized in non-staple sales being the lowest) suggest that households present, on average, greater levels of women's empowerment even when their sales portfolio is close to being mostly non-staple crops.

5.7. Additional Considerations

5.7.1 Share of non-staples sold among crop sellers

Table 15: Empowerment on non-staple share in total sales, conditional on selling any crop.

	Malawi	Ethiopia	Uganda	Tanzania	Nigeria
Cash crop share	-0.03	**-0.15***	-0.01	**-0.06**	0.03
	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)
Constant	**0.68***	**0.55**	**0.95***	**0.94***	**0.58**
	(0.12)	(0.27)	(0.06)	(0.07)	(0.3)
Observations	2,456	3,544	3,432	3,552	2,312
R-squared	0.49	0.62	0.76	0.54	0.71

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All models include household and time fixed effects with standard errors clustered at the household level. This regression is conducted only on households with a commercialization index greater than 0.01.

VI. CONCLUSION

This multi-country panel study (Ethiopia, Malawi, Tanzania, Uganda, Nigeria) examines how agricultural commercialization affects women's empowerment, separating extensive-margin effects (transition from non-seller to seller) from intensive-margin effects (how the sales mix—especially the share of non-staples/cash crops—modifies empowerment among sellers). Using household fixed effects, Double Machine Learning, and propensity-score matched difference-in-differences (PSM-DiD), we find that entering markets substantially raises the probability a household is classified as empowered, with PSM-DiD average treatment effects of +0.43 in Ethiopia, +0.29 in Malawi, +0.26 in Tanzania and +0.13 in Nigeria (ns in Uganda). Among existing sellers, adding cash crops also raises empowerment in Malawi (+0.14), with a smaller, marginal effect in Ethiopia.

At the intensive margin, commercialization's baseline association with empowerment is positive, but it weakens as the share of non-staples in sales rises (negative interaction) in Malawi, Ethiopia, and Tanzania; Uganda and Nigeria show null effects. These patterns are strongest for the income-decision domain of empowerment.

A non-linearity test that stratifies sellers into two diversification groups (below- vs above-average crop diversification) and four sales-mix bands shows concave returns: empowerment rises with commercialization across bands, but gains are larger for diversified producers and taper for "mostly non-staples" portfolios—still positive, just smaller. Overall, the results reconcile seemingly conflicting narratives: market entry empowers, yet strong specialization in high-value crops can erode those gains, especially for less-diversified producers.

Nigeria, the country with the highest GDP in our sample, presents only positive associations with empowerment and our sales-mix bands among the above-average diversification group.

VII. POLICY RECOMMENDATIONS

7.1 Leverage the extensive margin (getting households to sell) by strengthening the "Hidden Middle"

Empowerment gains are largest when new sellers cross the market threshold, and pre-trend and placebo tests lend more credible support to the extensive margin analyses; the biggest barriers are search, transport and post-harvest frictions. Midstream small and medium enterprises (SMEs) – processors, wholesalers, logistics firms and brokers – account for roughly 30–40 % of value added in food chains and their productivity is as important as on-farm yields. They move about 65 % of food consumed in Africa and South Asia and have proliferated rapidly, yet remain "hidden" from many policy debates (Reardon, 2015).

Investments in last-mile buying points, wholesale markets, third-party logistics and basic post-harvest services are therefore first-order levers for entry. Evidence from Nigerian maize traders shows that most traders own little transport or storage; instead they rely on a well-developed third-party logistics and warehouse rental market and sell grain already bagged (Liverpool-Tasie et al., 2017). Such services cut fixed costs for smallholders and enable initial sales. Among existing sellers, introduce cash crops gradually so that non-staple sales stay within a low-to-moderate share; this preserves the extensive-margin benefits while avoiding premature specialization.

Reardon, Liverpool-Tasie and Minten (2021) recommend investing primarily in infrastructure as *"SMEs are constrained by poor wholesale markets, bad roads, unreliable electrification and bribes on the roads"*, cutting red tape and professionalizing food-safety standards. Nigeria's maize traders illustrate how third-party logistics and warehouse rental markets enable smallholders to sell without owning capital. Expanding such midstream infrastructure beyond major cities, training brokers and wholesalers to aggregate smallholder output and enforcing transparent commercial practices will lower entry costs, support gradual diversification and amplify women's empowerment.

7.2 Program by diversification profile (the two groups)

Segment households by their production breadth and adapt interventions accordingly. For less-diversified households, promote staple-oriented strategies with modest cash-crop shares; bundling input packs and extension around mixed portfolios prevents empowerment returns from tapering when these households move quickly into non-staple dominance. For more-diversified households, facilitate higher non-staple shares, but monitor sales to prevent drifting into a "mostly non-staples" band where marginal empowerment returns shrink. Midstream services such as rental storage and logistics provide a low-risk way to test new crops (Liverpool-Tasie et al., 2017), so connecting broader-base households to these services enables controlled diversification.

In Nigeria, households can benefit from commercialization if they are more production-diversified, so programs that promote such practice are recommended.

7.3 Reinforce where gains are strongest

Because empowerment improvements concentrate in the income-decision domain, institutionalize women's role in financial choices. Integrate facilitated household financial dialogues, budgeting training, and transparent payment flows into value-chain projects so that commercialization's benefits translate into durable bargaining power within the household.

Evidence from Ethiopia shows that randomly allocating joint savings accounts (in lieu of single accounts) to cash-crop farming households increases savings and enhances women's decision-making authority over resources; women in joint-account households exhibit significant gains in bargaining power (Galdo, 2025). These results underscore the value of embedding joint payment options or women-titled accounts into commercialization programs. By ensuring that income from new market activities is deposited into shared or women-controlled accounts, programmes can strengthen women's control over household finances, complementing the extensive-margin and diversification strategies above.

7.4 Country-specific calibration and monitoring

Sequence interventions to local patterns. In Malawi, Ethiopia, Tanzania and Nigeria, prioritize extensive-margin entry support via midstream logistics and infrastructure investments (wholesale markets, roads, electrification). In Uganda, where already most producers are empowered, and with a seemingly null association with commercialization, alongside a negative correlation with entry to the markets, focus should be in promoting off-farm income and strengthening the Hidden Middle, to sustain those levels of empowerment. Across all settings, monitor sales mixes by quartile and diversification groups; flag when portfolios approach "mostly non-staples" and activate guardrails such as joint payment adoption or diversification incentives.

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APPENDIX

A. Additional tables

Table A. Pillars for our women's empowerment index (adapted from A-WEAI)

Pillar	Common Questions Used Across Countries
Production: Input in productive decisions (1/4)	- Who makes primary decisions on crops, inputs, and timing of activities on fields? / Who is the primary decision maker? - Who decides on the use of crop output? - Who makes decisions about selling crops and/or livestock? - Who owns this enterprise in the household? / Who manages the enterprise?
Resources: Ownership of assets (1/6)	- Who owns specific assets (e.g., parcels, livestock, equipment, durable assets)?
Resources: Access to and decisions on credit (1/12)	- Which household member was responsible for the loan?
Income: Control over use of income (1/4)	- Who makes decisions regarding earnings from enterprises? - Who kept/decided what to do with money from various sources (transfers, rental income, sale of assets, etc.)? - Who decides on use of income earned from selling crops? / byproducts? - Who decides on use of income earned from sale of livestock products? / byproducts?
Time: Workload (1/4)	- Hours worked in various activities over the past week (adequate if all females in the household work less than 50 hours per week if older than 15, if younger, then less than 9 hours/week). Based on Bardasi & Wodon (2006).

Table A2. Mean values of key variables between disempowered versus empowered households (standard errors in parentheses). Low-income countries.

Income Stratum	Low		Low		
	Ethiopia		**Malawi**		
Variable	**Disempowered**	**Empowered**	**Disempowered**	**Empowered**	
Household Characteristics					
Commercialization index	0.15	0.18***	0.09	0.14***	
	(0.00)	(0.00)	(0.00)	(0.00)	

Share of food consumed purchased	0.41	0.44***	0.53	0.53
	(0.00)	(0.01)	(0.01)	(0.00)
Share of off-farm income	0.17	0.21***	0.79	0.78
	(0.00)	(0.01)	(0.01)	(0.01)
Below poverty line	0.60	0.59	0.43	0.32***
	(0.01)	(0.01)	(0.01)	(0.01)
Consumption quintile	2.89	2.84*	2.90	2.98**
	(0.02)	(0.02)	(0.03)	(0.02)
Head of household's age	45.73	47.27***	43.91	43.24*
	(0.19)	(0.24)	(0.31)	(0.24)
Head is male	0.86	0.64***	0.84	0.68***
	(0.00)	(0.01)	(0.01)	(0.01)
Avg. Years of educ. of HH workforce	2.04	2.53***	4.79	5.58***
	(0.03)	(0.05)	(0.07)	(0.06)
Dependency ratio	3.14	2.88***	1.17	1.18
	(0.02)	(0.03)	(0.02)	(0.02)
Household size	5.36	4.89***	4.93	4.99
	(0.03)	(0.04)	(0.04)	(0.03)
Meso Variables				
Road Density	11.86	12.71**	24.58	29.28***
	(0.26)	(0.28)	(0.31)	(0.28)
Farm Characteristics				
Cultivated area (ha)	1.44	1.39	0.72	0.76**
	(0.03)	(0.04)	(0.01)	(0.01)

Note: *** p<0.01, ** p<0.05, * p<0.1 indicate significant differences between empowered and disempowered groups within each country.

Table A3. Mean values of key variables between disempowered versus empowered households (standard errors in parentheses). middle- and high-income countries.

Income Stratum	Middle		Middle		High	
	Tanzania		Uganda		Nigeria	
Variable	Disemp.	Emp.	Disemp.	Emp.	Disemp.	Emp.
Household Characteristics						
Commercialization index	0.22	0.30***	0.26	0.27	0.23	0.28***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.05)
Share of food consumed purchased	0.60	0.54***	0.50	0.46***	0.68	0.70***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Share of off-farm income	0.65	0.55***	0.79	0.73	0.43	0.58***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Below poverty line	0.54	0.54	0.64	0.66	0.36	0.28***
	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Consumption quintile	2.51	2.54	2.8	2.90***	2.53	2.69***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Head of household's age	47.12	49.05***	45.6	47.8***	50.28	52.80***
	(0.25)	(0.24)	(0.40)	(0.22)	(0.22)	(0.25)
Head is male	0.85	0.67***	0.85	0.67***	0.97	0.84***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Avg. Years of educ. of HH workforce	3.90	3.71***	6.07	6.13	3.47	5.02***
	(0.05)	(0.05)	(0.1)	(0.05)	(0.08)	(0.06)
Dependency ratio	1.14	1.24***	1.89	1.78**	1.02	0.93***
	(0.01)	(0.02)	(0.04)	(0.02)	(0.01)	(0.01)
Household size	5.66	5.46***	5.5	5.98***	5.8	6.23***
	(0.05)	(0.04)	(0.07)	(0.04)	(0.05)	(0.07)
Meso Variables						

Road Density	11.51	8.77***	23.13	24.82***	14.99	18.27*** (0.24)
	(0.19)	(0.13)	(0.33)	(0.23)	(0.27)	
Farm Characteristics						
Cultivated area (ha)	2.20	2.48***	1.13	1.37***	1.54	1.25***
	(0.06)	(0.06)	(0.04)	(0.03)	(0.03)	(0.027)

Note: *** p<0.01, ** p<0.05, * p<0.1 indicates significant differences between empowered and disempowered groups within each country.

Table A4. Most recent survey wave, percentage of households empowered in each dimension.

Country	Productive Decisions (%)	Income Use (%)	Asset Ownership (%)	Credit Access (%)	Workload (%)
Ethiopia	66	86	93	17	88
Malawi	90	76	68	18	94
Tanzania	75	52	75	21	83
Uganda	94	74	86	-	90
Nigeria	83	52	89	62	90

B. Additional regression results

Table B1. Two-way fixed effects regressions: A-WEAI dimensions on commercialization index (cci) and interaction with cash-sale share, by country.

Panel A: Input in Productive Decisions

	ETH	MLW	TZN	UGD	NGR
Commercialization Index (0–1)	0.86*** (0.08)	0.00 (0.04)	-0.02 (0.03)	-0.01 (0.02)	-0.10*** (0.03)
Comm. Index × Cash-sale Share (0–1)	-0.59*** (0.09)	-0.07 (0.06)	-0.08** (0.04)	0.00 (0.03)	0.12** (0.06)

Panel B: Input in Income Decisions

	ETH	MLW	TZN	UGD	NGR
Commercialization Index (0−1)	0.45*** (0.07)	0.46*** (0.06)	0.45*** (0.03)	-0.01 (0.04)	0.18*** (0.04)
Comm. Index × Cash-sale Share (0−1)	-0.19** (0.08)	-0.06 (0.07)	-0.19*** (0.04)	0.03 (0.04)	0.00 (0.07)

Panel C: Ownership of Assets

	ETH	MLW	TZN	UGD	NGR
Commercialization Index (0−1)	0.07 (0.05)	-0.04 (0.05)	-0.03 (0.03)	0.01 (0.03)	0.06* (0.03)
Comm. Index × Cash-sale Share (0−1)	-0.02 (0.06)	0.02 (0.07)	0.00 (0.03)	-0.01 (0.04)	-0.13** (0.06)

Panel D: Control Over Credit

	ETH	MLW	TZN	UGD	NGR
Commercialization Index (0−1)	-0.10 (0.07)	0.04 (0.04)	-0.04* (0.02)	—	0.00 (0.05)
Comm. Index × Cash-sale Share (0−1)	0.13* (0.07)	-0.08 (0.05)	0.07** (0.03)	—	0.06 (0.09)

Panel E: Time Allocation

	ETH	MLW	TZN	UGD	NGR
Commercialization Index (0−1)	-0.06 (0.05)	0.00 (0.02)	-0.05* (0.03)	-0.04 (0.03)	-0.01 (0.03)
Comm. Index × Cash-sale Share (0−1)	0.05 (0.05)	0.04 (0.04)	0.01 (0.03)	0.03 (0.04)	0.08 (0.05)

*Note: (Robust SEs clustered at household; FE for household and time. "—" = not available.) Stars: * p<0.10, ** p<0.05, *** p<0.01. Values rounded to* **two decimals***.*

C. Quasi-experiment pre-trend and placebo tests

Table C1. Event-study (parallel trends) diagnostics by country and analysis

(Pre-trend joint test: H0 = all pre-treatment effects = 0; verdict uses p ≥ 0.10 = PASS)

Country	Analysis	Pre-trend χ²(df), p	Verdict (pre)	Post dynamics χ²(df), p	Note
Malawi	Entry to the market (non-selling -> selling)	2.197 (4), 0.700	**PASS**	12.088 (3), 0.007	Post dynamics significant
Malawi	Cash crop sales adoption (only sales staples -> sells some cash crop)	2.702 (4), 0.609	**PASS**	2.103 (3), 0.551	—
Ethiopia	Entry to the market (non-selling -> selling)	—	N/A (2 periods; no pre)	40.654 (1), 0.000	Only two waves (2014, 2016)
Ethiopia	Cash crop sales adoption (only sales staples -> sells some cash crop)	—	N/A (2 periods; no pre)	3.509 (1), 0.061	—
Uganda	Entry to the market (non-selling -> selling)	4.07 (4), 0.397	**PASS**	8.86 (5), 0.112	No post-trend dynamics
Uganda	Cash crop sales adoption (only sales staples -> sells some cash crop)	significant pre at t − 6, p=0.025	**FAIL**	t+4 significant (p=0.026; t+8 ≈ 0.093)	Post mixed
Tanzania	Entry to the market (non-selling -> selling)	1.696 (4), 0.791	**PASS**	27.616 (4), 0.000	Post dynamics significant
Tanzania	Cash crop sales adoption (only sales staples -> sells some cash crop)	2.815 (4), 0.589	**PASS**	3.249 (4), 0.517	—
Nigeria	Entry to the market (non-selling -> selling)	0.245 (1), 0.621	**PASS**	3.198 (2), 0.202	—

Nigeria	Cash crop sales adoption (only sales staples -> sells some cash crop)	0.055 (1), 0.815	**PASS**	3.922 (2), 0.141	—

Table C2. Placebo DID falsification tests by country, analysis, and cohort

(Verdict uses p ≥ 0.10 = PASS. "Baseline-difference" used for only 2 periods.)

Country	Analysis	Cohort → Placebo year	Coef	SE	p	Verdict	Method
Malawi	Entry to the market	2016 → 2013	−0.0470	0.1060	0.6579	**PASS**	DID-pre-only
		2019 → 2016	−0.0351	0.0882	0.6907	**PASS**	DID-pre-only
Malawi	Cash Crop sales adoption	2016 → 2013	0.0645	0.1230	0.6003	**PASS**	DID-pre-only
		2019 → 2016	−0.0592	0.0827	0.4741	**PASS**	DID-pre-only
Ethiopia	Entry to the market	2016 → 2014	−0.0433	0.0373	0.2455	**PASS**	Baseline-difference
Ethiopia	Cash Crop sales adoption	2016 → 2014	−0.0919	0.0440	0.0367	**FAIL**	Baseline-difference
Uganda	Entry to the market	2016 → 2014	0.0663	0.0962	0.4919	**PASS**	DID-pre-only
		2020 → 2016	0.0293	0.1224	0.118	**PASS**	DID-pre-only
		2014 → 2012	0.303	0.109	0.006	**FAIL**	DID-pre-only
Uganda	Cash Crop sales adoption	2016 → 2014	0.0125	0.0529	0.8111	**PASS**	DID-pre-only

		2020 → 2016	−0.0152	0.0602	0.8013	**PASS**	DID-pre-only
Tanzania	Entry to the market	2015 → 2013	0.0062	0.0663	0.9262	**PASS**	DID-pre-only
		2020 → 2015	0.2568	0.1531	0.0945	**FAIL**	DID-pre-only
Tanzania	Cash Crop sales adoption	2015 → 2013	0.1236	0.0682	0.0707	**FAIL**	DID-pre-only
		2020 → 2015	−0.1401	0.1308	0.2847	**PASS**	DID-pre-only
Nigeria	Entry to the market	2019 → 2016	−0.0386	0.0619	0.5332	**PASS**	DID-pre-only
Nigeria	Cash Crop sales adoption	2019 → 2016	−0.0192	0.0557	0.7300	**PASS**	DID-pre-only

Table C3. Pre-trend tests for staggered adoption models

Country	Entry to the markets pretrend χ²(df); p	Selling cash crops pretrend χ²(df); p
Malawi	0.335 (1); 0.563	1.170 (1); 0.279
Tanzania	1.570 (1); 0.210	1.098 (1); 0.295
Uganda	1.748 (3); 0.626	0.806 (3); 0.848
Nigeria	N/A (df=0); N/A	N/A (df=0); N/A

Note: H0: All pre-treatment effects = 0

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