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Does securing the commons conserve resources and improve well-being?

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Abstract

Policies to secure property rights extend over hundreds of millions of hectares of land claimed as common property. Well-being and resource outcomes from securing the commons are theoretically shown to vary, conditional on local institutional quality and the extent of resource dependence among policy recipients. A differences-in-differences framework is applied to micro-scale panel data to evaluate the impacts of securing forest commons in Malawi. We find short-term negative effects on food security and non-food expenditures but no impact on forest loss rates. Baseline institutional capacity and households' labour portfolios are empirically shown to condition outcomes, with implications for policy targeting.

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1 Introduction

Up to 50% of land in low- and middle-income countries, including land under cultivation as well as natural ecosystems, is claimed *de facto* as common property by indigenous groups and other communities (Rights and Resources Initiative, 2023). Such claims have, since the 1980s, increasingly been made more secure via land titling and policies that transfer the legal rights to exploit and manage common-pool resources from governments to communities. Securing the commons, in principle, provides incentives to invest in the collective management of the commons sufficient to minimise the risk of free riding, conserve resource stocks and raise the returns from resource extraction.[1] Raising extraction returns could improve the well-being of resource users yet to be effective, efforts to secure the commons must ensure that a potential increase in incentives associated with resource extraction, via more secure access and withdrawal rights, does not lead to increased pressures on resource stocks, that is, via more secure management and exclusion rights.

As a property rights approach, securing the commons effects changes in institutional arrangements, the outcomes of which are subject to conditions that are often also institutional in nature. Potential beneficiaries typically depend on resources for their incomes and livelihoods, and have limited outside options due to, e.g. a lack of human capital and poorly functioning labour markets. Yet, low returns to resource extraction due to, e.g. a lack of scale and missing input markets, are exacerbated by unclear tenurial and usufruct arrangements as well as weak community institutions for enforcing *de facto* rights. In this paper, these conditions are theoretically and empirically shown to help explain variation in the resource and well-being outcomes from policies to secure the commons, at the micro-scale.

We begin with a theoretical model in which securing management and exclusion rights incentivises external investments in the community's capacity to regulate the extent of labour to resource extraction allocated by, respectively, community members and non-members, while securing access and withdrawal rights incentivises investments in resource production (Section 2). The model's outcomes turn on changes to the average returns from resource extraction, a function of resource production and labour allocated to extraction by members and non-members. We find that although effective improvements in the community's capacity to regulate labour to extraction could move the commons away from open access, potentially reducing rates of resource degradation, there are ambiguous effects on members' well-being. Securing the commons is likely to conserve resources *and* improve well-being when effective investments in resource production are implemented alongside

[1] Under certain conditions, secure communal (or joint) ownership of private property (Hart, 1995) or public goods (Besley & Ghatak, 2001) is optimal. Also well-established are the conditions under which common-pool resources are more efficiently managed as common than as state or private property, including the need for secure, durable property rights (Ostrom, 1990; J. Baland and Platteau, 1996; Agrawal, 2001).

effective efforts to improve the community's capacity to regulate labour to extraction. An impactful policy is expected when the community's *ex ante* capacity to regulate labour to extraction is weak, and where members are highly dependent on extraction for their incomes and livelihoods.

Our theory is tested with an empirical evaluation of the well-being and forest outcomes from the Improved Forest Management for Sustainable Livelihoods Programme (IFMSLP), a community forest management scheme[2] implemented in Malawi, where resource-dependent livelihoods are common and a high incidence of poverty reflects the critical role of forests as a safety net for the rural poor (Jumbe and Angelsen, 2006; Mazunda and Shively, 2015; Meyer, 2023). Specifically, we evaluate the IFMSLP between 2012 and 2014 when communities received legal rights to access, withdraw and manage forest resources, as well as exclusion rights. These rights applied to the exploitation and management of forests both in Forest Reserves, a type of protected area, and customary forest areas outside the Reserves (Section 3).

The well-being and forest impacts of the IFMSLP are evaluated at the household scale. We adopt three measures of well-being: a measure of food security, the Food Consumption Score (World Food Programme, 2008), value of assets, and non-food expenditures. Forest loss is measured within range of the average distance a household walks to collect fuelwood during a single trip. A panel dataset, described in Section 4, is constructed from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture, specifically four rounds of longitudinal household data (2010, 2013, 2016, 2019) from the Integrated Panel Household Surveys for Malawi, combined with forest loss data from the Global Forest Change dataset (Hansen et al., 2013). Observations recorded in 2010 are utilised as our baseline to evaluate the impacts in 2016 and 2019. To infer a causal relationship between the IFMSLP and outcomes, we create a control group comprising households resident in communities not selected into the IFMSLP and apply a differences-in-differences framework to our dataset. We lack information regarding precisely how communities were selected to participate in the IFMSLP yet suggestive of selection bias, the legislation underlying the policy focuses on improving livelihoods (Government of Malawi, 1996; Government of Malawi, 2003). Indeed, in 2010 the treated group was poorer and lived in remoter areas with higher forest cover than the control group, motivating the application of Propensity Score Matching.

Our results in Section 5 show that the IFMSLP reduced food security and non-food expenditures in 2016, respectively, by 17% (of the FCS sample mean) and 57%. These effects had mostly dissipated, but not reversed, by 2019. Distinguishing between Forest Reserves and customary areas, we observe no effect on rates of forest loss. The biggest threat to identification is our lack of

[2] There are numerous terms for this type of scheme, e.g. Forest Co-management (typically implemented in protected areas), Community-based Forest Management, Participatory Forest Management.

pre-treatment trend data, to which we apply several checks. We re-run the DiD estimator using the 2013 outcomes, condition on covariates via application of the doubly-robust estimator to our data (Sant'Anna & Zhao, 2020), and capture background development trends via the inclusion of community-level matching variables. Our results also remain robust to the application of further checks, including alternative compositions of the household sample and treatment areas, different matching algorithms, spillovers between treated and control groups, and the possibility that our results are driven by extreme weather events.

Reassured that our main results are driven by the IFMSLP, we investigate whether they are conditioned by the strength of the community's capacity to regulate labour to extraction, and the extent of resource dependence among members, prior to receiving legal rights. In Section 6, we first group households according to whether they resided in communities with a common property claim in 2010, under the assumption that community capacity to regulate labour to extraction is unlikely to exist in the absence of a claim. Results show that households in a community without a claim were more likely to experience a fall in well-being than those in one with a claim. Next, we create groups of households based on their labour allocation in 2010, differentiating among households who allocated their labour to fuelwood collection and subsistence agriculture, and those with outside options. Our results suggest that the decline in the FCS was concentrated among the former while the fall in non-food expenditures was found among the latter.

Our study contributes to a theoretical literature, mostly focused on forest commons, e.g. Alix-Garcia et al. (2005), J.-M. Baland and Francois (2005), Brunette et al. (2020), and Delacote (2009), which considers common-pool resource extraction as one of several activities in an agent's income-earning portfolio. Building on previous work by J.-M. Baland and Francois (2005) and Delacote (2009) on the conditions under which resource extraction serves as a either a safety net or a poverty trap, we integrate such a portfolio into a property rights framework.[3] In focusing on well-being, we abstract from a proper consideration of resource outcomes, typically modelled via resource stock dynamics. Although previous models have examined the impact of securing the commons on resource sustainability, e.g. Copeland and Taylor (2009), Noack and Costello (2024), the standard assumption is that resource extraction is the sole activity in agents' portfolios. Perhaps closest to our framework, with a focus on well-being in a constrained institutional setting but with the inclusion of resource stock dynamics, is Noack et al. (2018), who examined how secure access rights can induce labour reallocation from resource extraction to resource-independent production. We include access rights in a broader set of property rights to demonstrate how baseline institutional capacity and household labour portfolios condition outcomes when the commons is secured.

[3]The role of an agent's portfolio of labour opportunities in the context of open access and private property in forest settings has been explored theoretically in the literature, at least since the work of Angelsen (1999).

Also focused on resource outcomes is a literature that employs panel data and quasi-experimental methods to evaluate policies to secure forest commons (Hajjar et al., 2021; Miller et al., 2021; Tseng et al., 2021; Balboni et al., 2023). Consistent with our results, some of these studies found no effect on forest, for example, land titling schemes that conferred collective rights in Brazil (BenYishay et al., 2017), Ecuador (Buntaine et al., 2015) and Indonesia (Kraus et al., 2021). Other studies found reductions in forest loss via, e.g. land titling in Benin (Wren-Lewis et al., 2020), Brazil (Baragwanath & Bayi, 2020) and Peru (Blackman et al., 2017), as well as community forest management in Thailand (Chankrajang, 2019). Less attention has been paid to the well-being of those exploiting and managing the commons. Contrary to our results, previous research has demonstrated positive effects from, e.g. land titling in Colombia (Peña et al., 2017) and community forest management schemes in Tanzania (Pailler et al., 2015).[4] Given that securing the commons enables legal resource extraction, neglecting either forest or well-being overlooks the high likelihood of a close relationship between outcomes (see e.g., Barbier, 2010; Lade et al., 2017; Barbier and Hochard, 2019). Such a relationship is implied by Oldekop et al. (2019), who found positive poverty and forest outcomes in Nepal's community forest management scheme, and evidence of a trade-off between alleviating poverty and conserving forest where baseline poverty levels were high. Their unit of analysis, the sub-district, precludes further analysis of what might be driving their results. Indeed, more generally, where discussed in previous studies, what might help explain observed outcomes at the micro-scale has neither been theoretically nor empirically investigated in an economic framework.

We develop a framework to demonstrate how baseline community capacity to regulate labour to extraction and members' labour portfolios condition the outcomes of policies to secure the commons. Collectively, these policies cover around 30% of forests in LMIC (Rights and Resources Initiative, 2023),[5] some of which are also classified as protected areas, as in Malawi, with implications for the conservation of biodiversity and carbon stocks.[6] Schemes like Malawi's IFMSLP are often the product of wholesale changes in how natural resources are governed, specifically the processes of decentralization and devolution, which often formalise pre-existing *de facto* common property regimes (Ostrom, 1990; J. Baland and Platteau, 1996; Engel et al., 2013; Mansuri and Rao, 2013). Unlike land titling schemes, poverty alleviation is central to policies like the IFMSLP, hence the emphasis on efforts to raise the returns from resource extraction by, e.g. providing capital inputs. Discussed in Section 7, our study contributes to our understanding of efforts to improve well-being

[4]Early research examined a pilot precursor to the IFMSLP in two of Malawi's Forest Reserves yet with control groups resident in treatment areas likely biasing the estimated effects. Jumbe and Angelsen (2006) found mixed impacts on incomes while Mazunda and Shively (2015) found positive forest outcomes but no change in incomes.

[5]This includes forest that is defined as being legally controlled as common property across 73 surveyed countries (withdrawal, access, management, exclusion rights) as well as forest with limited rights (Rights and Resources Initiative, 2023).

[6]This trend, of common property rights superimposed on protected areas has, with exceptions (e.g. Bonilla-Mejía and Higuera-Mendieta, 2019 for Colombia), largely been neglected in the protected area literature except in the context of multiple-use protected areas and variation in protection type (see Reynaert et al., 2024).

among the one billion people globally who derive benefits from forests, including contributions to livelihoods and incomes, as well as nutritional, energy and housing needs (Angelsen and Wunder, 2003; Angelsen et al., 2014; Wunder et al., 2014; Shyamsundar et al., 2020).

2 A model of common-pool resource extraction

This section presents a theoretical framework on the potential impacts of securing the commons with respect to household well-being and resource outcomes. Consistent with our study period, we consider short-run impacts only and present a static model. We begin by describing the model set-up in the baseline before showing how securing the commons could influence outcomes. Technical details of the model, including all proofs, are presented in Appendix A.

2.1 Model set-up

Consider a community, represented as a continuum of community members $i \in [0,1]$, who allocate a share l_i of their labour to common-pool resource extraction and a share $(1-l_i)$ to their outside option, e.g. wage labour. We introduce two institutional variables, which regulate the amount of labour to resource extraction. First, the strength of *de facto* exclusion rights reflects the community's capacity to regulate the extent of access to, and withdrawal of, resource benefits by non-members. Parameter L_e is the amount of labour allocated by non-members to extraction. Lower (higher) L_e implies a stronger (weaker) capacity to exclude non-members from extraction benefits. Second, the strength of *de facto* management rights reflects the community's capacity to regulate the amount of labour allocated by members to resource extraction (assuming that these limits are respected): $l_i \leq \overline{l_i}$. Total labour allocated by members to extraction is thus also limited: $L_i = \int_0^1 l_i d_i \leq \overline{L_i} = \int_0^1 \overline{l_i} d_i$. Lower (higher) $\overline{l_i}$ represents a higher (lower) capacity to regulate extraction. When $\overline{l_i} = 1$, there are no constraints on extraction by members.

Combining both lower (higher) L_e and lower (higher) $\overline{l_i}$ implies a lower (higher) likelihood of open access and resource degradation in the commons.

Total labour allocated to resource extraction is the sum of labour allocated by members and non-members: $L = L_i + L_e$. Overall, the return from extraction for member i is: $l_i e \frac{Y(L)}{L}$, with $Y(L)$ denoting the extraction production function and $l_i \leq \overline{l_i}$. Similar to J.-M. Baland and Francois (2005) and Delacote (2009), $\frac{Y(L)}{L}$ equals average productivity across all resource users in the commons, including both members and non-members. The return from the outside option is given by $\theta_i A(l_i)$, with θ_i a productivity parameter, and $A(l_i)$ the production function of the member's outside option, with $A'(l_i) < 0$ and $A''(l_i) > 0$.

Community member i allocates her labour to maximize her net income (Appendix A). Assuming that members do not take into account the impact of their labour allocation on the return to resource extraction, the first-order conditions on the Lagrangian implicitly give the equilibrium labour allocation, l_i^*. In equilibrium, three groups of community members can be distinguished: *unskilled members*, with low productivity θ_i, are constrained by (effective) management of the commons and would prefer to allocate more labour to extraction;[7] *mid-skilled members*, with medium productivity θ_i, allocate their labour between their outside option and extraction, and; *skilled members*, with high productivity θ_i, allocate all their labour to their outside option.

Total labour allocated to resource extraction comprises labour from unskilled and mid-skilled members, as well as labour allocated by non-members (Appendix A).

2.2 Securing the commons

Securing the commons confers or transfers legal access, withdrawal, management, and exclusion rights to communities claiming a commons.[8] Secure rights could, in principle, incentivise external investments to improve the community's capacity to exclude non-community members (from appropriating resource benefits) and manage the commons more sustainably on behalf of community members, and improve resource production. In our model set-up, securing the commons is thus characterised as external investments that potentially: strengthens community capacity to exclude non-members from the commons; strengthens community capacity to manage the commons internally; and/or, increases resource production.

We begin with exclusion and management rights, which remain under the authority of community institutions for the purpose of monitoring and enforcing the rules established to govern resource extraction, that is, to determine access and withdrawal rights and their correlated duties.[9] Exclusion rights, if effective, restrict the amount of labour allocated to resource extraction by non-members, directly influencing the average return to extraction, $\frac{Y(L)}{L}$. This direct effect is followed by an indirect effect in terms of labour allocated to extraction by members. Strengthening the community's capacity to exclude non-members (reducing L_e) thus decreases labour allocated by non-members and increases the total amount of labour allocated by members to extraction (Ap-

[7]This is consistent with evidence from the literature showing that the extraction of forest products in the commons, characterised by low returns due to, e.g. lack of scale, low labour productivity, and missing markets, is typically undertaken by poorer and less-skilled households (Dasgupta and Mäler, 1995; Reddy and Chakravarty, 1999).

[8]Community institutions typically determine rules for resource extraction and use, which specify both the rights (access and withdrawal) and duties of community members and non-members (Schlager & Ostrom, 1992). Duties are restrictions on access and withdrawal specified by management and exclusion rules. We note other ways to impose duties, e.g. ostracism, but formal mechanisms are more commonly used to enforce exclusion rights (Agrawal, 2001).

[9]Sufficient authority is required for management and exclusion rights to be effective (see, e.g. Chhatre and Agrawal, 2008, Gibson et al., 2005). Investments in a community's capacity to manage the commons and exclude non-members often seek either to establish new community institutions or strengthen pre-existing ones, e.g. the *conseil du village* in Benin (Wren-Lewis et al., 2020), Forest User Groups and Forest User Cooperatives in Ethiopia (Gelo & Koch, 2014).

pendix A). Should members fail to internalize the negative impact of their labour allocation on the return from extraction, total labour to extraction potentially increases, depending on the distribution of θ_i in the population and the shape of the resource production function, $Y(L)$. Further, the extent of these effects depends on the relative strength of the community's *de facto* exclusion rights (and hence, the community's baseline capacity to exclude), the effectiveness of efforts to strengthen the community's capacity to exclude, and the distribution of private productivity.

When exclusion rights are effectively secured, the well-being of skilled members remains unchanged while the well-being of unskilled and mid-skilled members depends on the extent of direct and indirect effects, that is, on the balance of changes in the total amount of labour allocated to resource extraction. This balance determines whether average returns to extraction, $\frac{Y(L)}{L}$, increases or decreases. The extent to which members' labour to extraction replaces that of non-members depends on the strength of the community's *de facto* management rights and the extent of myopic behaviour among community members: where management rights remain weak and members myopic, total labour to extraction increases, the average returns to extraction fall and the well-being of unskilled and mid-skilled members declines. Less myopic behaviour, on the other hand, could lead to an increase in members' labour to extraction that does not equal, or exceed, the decline in non-members' labour thus raising average returns to extraction and members' well-being.

Limiting, or even reducing, members' total labour to extraction could be achieved by strengthening the community's capacity to manage the commons, reducing $\overline{l_i}$. The extent of decline in labour to extraction depends on the relative strength of the community's *de facto* management rights, that is, the community's capacity to manage the commons in the baseline, as well as the effectiveness of efforts to improve this capacity.[10] Improving a community's management capacity is expected to reduce the well-being of unskilled members (Appendix A).[11] This outcome is more likely, if, similar to the previous situation in which exclusion rights were made effective but not management rights, the community's management capacity improves while its capacity to exclude non-members remains weak (and unchanged) leading to a rise in non-members' allocation of labour to extraction.

The net effects of strengthening the community's capacity to exclude and/or its capacity to manage the commons on well-being and resources thus largely depend first, on the relative strength of *de facto* exclusion and management rights and second, on skills endowments among members. For changes in outcomes to materialise, baseline *de facto* exclusion and/or management rights should be weak, not strong. From a baseline of weak *de facto* rights, effective improvements, both

[10] One implication is that while strengthening community capacity to exclude non-members may decrease inequalities, a stronger capacity to manage the commons internally tends to increase them.

[11] Note that given our focus on short-term effects, we do not account for the possibility that strengthening a community's management capacity could help to secure the commons in the long run, potentially benefiting members dependent on resource extraction for their incomes and livelihoods.

in the community's capacity to exclude non-members and capacity to manage the commons, are likely to reduce the likelihood of open access and resource degradation. The implications for well-being are more nuanced, although under all scenarios the group most likely to be impacted are the unskilled members. When both *de facto* exclusion and/or management rights are effectively secured, these members could be better or worse off depending on the extent to which the direct effects dominate the indirect effects (see Figure 1). If exclusion rights are secured more effectively than management rights, the well-being of unskilled members is expected to increase. Conversely, when management rights are secured more effectively than exclusion rights, unskilled well-being is likely to decline. In the latter scenarios, in which either exclusion or management rights are secured, we do not anticipate any change to resource degradation rates: partial regulation of labour to extraction implies a lower likelihood of shifting away from open access.

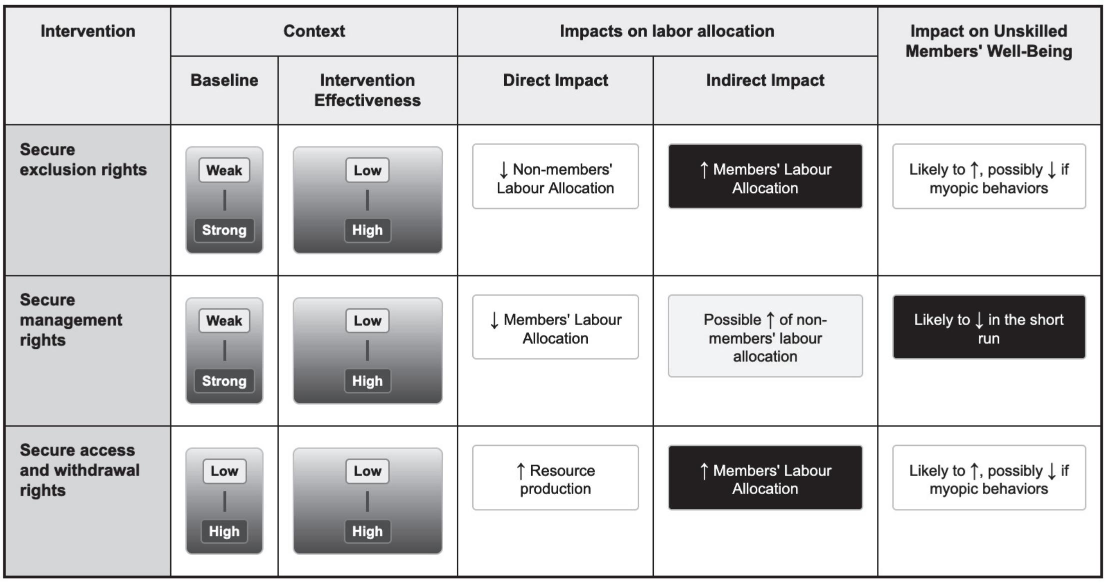

Figure 1: Impact of securing the commons on unskilled members' well-being

Additional to regulating labour to extraction, the average returns to extraction could be increased by securing access and withdrawal rights, potentially generating incentives for investments in boosting $Y(L)$.[12] Investments to improve resource production are denoted by the factor $\gamma > 1$.[13] Although inclusion of $\gamma > 1$ in the community member's objective function directly affects $Y(L)$, it also changes the allocation of labour. The net effect on well-being depends on the strength of

[12]More secure access and withdrawal rights, which are usually conferred on households or individuals by community institutions, often formalize pre-existing *de facto* rights. Securing such rights have been shown to, for example, facilitate more secure access to resources in disputed territorial claims, such as protected areas in Indonesia (Engel et al., 2013), and enable market access for extracted products, such as non-timber forest products in Ethiopia's community forest management scheme (Gelo & Koch, 2014). Secure rights could also facilitate capital investment in the commons, e.g. in bee-keeping and forestry activities in Tanzania (Pailler et al., 2015).

[13]Increased access to credit targeted to resource extraction could help households invest in more efficient extraction technologies. Non-targeted access to credit as in Noack and Costello (2024) would reshape the activity portfolio, as shown by Combes et al. (2018).

baseline *de facto* access and withdrawal rights, the effectiveness of efforts to boost $Y(L)$, the extent of myopic behaviour among members, the strength of *de facto* exclusion and management rights, and the effectiveness of efforts to strengthen the latter. For instance, if $Y(L)$ is boosted while management capacity remains weak, members behaving myopically will allocate more labour to extraction, reducing $\frac{Y(L)}{L}$ and hence, their well-being (Appendix A). As shown in Figure 1, securing access and withdrawing rights has impacts on well-being similar to those from improving the community's capacity to exclude non-members. In sum, securing the commons is most likely to both conserve resources and improve well-being when resource extraction, among both members and non-members, is effectively regulated and resource production effectively boosted.

3 Background to the IFMSLP in Malawi

Ranked 174 out of 187 in the Human Development Index (UNDP, 2014), Malawi is one of the poorest countries in the world. In 2014, our final treatment year, 61.6% of the population lived below the income poverty line (PPP $1.25/day), with 29.8% living in severe poverty. The country is regularly exposed to floods and dry spells, which reduce agricultural productivity and contribute to food insecurity (Remme et al., 2015; McCarthy et al., 2021). Indeed, half to three-quarters of rural households in Malawi suffer from inadequate food each year (MNSO, 2005, 2012, 2017). Rural incomes and livelihoods are heavily resource dependent, typically involving own-farm production, fuelwood and water collection, and casual off-own-farm labour known as *ganyu*.[14]

Tree cover in Malawi fell from 16% in 2000 to 13% in 2020, with agricultural conversion and the demand for fuelwood and charcoal identified as the main drivers of deforestation and forest degradation (e.g., Jagger and Perez-Heydrich, 2016; Abman and Carney, 2020). Malawi's national government began the process of devolving forest management with the National Forest Policy (1996) and Forest Act (1997) leading to the National Forest Programme, launched in 2001 (Government of Malawi, 1996; Government of Malawi, 2003). This process effected a shift from unambiguous forest protection towards a participatory approach to forest management with a focus on supporting and improving rural livelihoods. In 1996, the Forest Co-management programme was piloted by Malawi's Government in two Forest Reserves (Jumbe and Angelsen, 2006, Mazunda and Shively, 2015).[15] Building on the pilot programme but scaled up nationally, the devolution process culminated with the IFMSLP. Implemented by Malawi's government in 12 districts, the IFMSLP was

[14]Undertaken by men, women and children, on behalf of other farmers, *ganyu* is widespread in Malawi (Bouwman et al., 2021). After own-farm production, *ganyu* is the most important livelihood strategy of rural households (Coulibaly et al., 2015; Whiteside, 2000), particularly for those with smaller land holdings unable to meet their consumption needs through own-farm production (Holden, 2014; Mtika, 2001). Common *ganyu* tasks include land preparation prior to the growing season and weeding during the growing season, usually undertaken as piecework, paid in cash or in kind (Whiteside, 2000).

[15]Malawi's Forest Reserves allow mixed uses, including resource extraction, and hence tend to have a lower level of *de jure* protection compared to National Parks.

implemented over two phases (2005-2010 and 2012-2014), which were designed and announced prior to the start of phase I. With almost €25 million of financial support provided by the European Union, the stated goals of the IFMSLP in phase I were to increase household incomes and improve food security through sustainable forest management (Olivier and Mwase, 2012). In phase II, these goals were subsumed under a broader aim of poverty reduction and with forest conservation made explicit (Remme et al., 2015). Although the aims of the IFMSLP were amended between phase I and II, the policy approach remained the same.

The IFMSLP provided village communities with the legal rights to access, withdraw and manage forest resources, as well as exclusion rights in designated areas within 18 Impact Areas established during phase I.[16] These Impact Areas were retained in phase II, with each one comprising at least one Forest Reserve and its surrounding buffer zones. Several communities were typically found in the buffer zone of a given Reserve. For each community, designated areas included a 'Block' in a Forest Reserve and a 'Village Forest Area' previously claimed as customary land in the Reserve buffer zone. During phase I, participation in the IFMSLP was restricted to households resident in communities located in buffer zones within 5km of the borders of Forest Reserves (Olivier and Mwase, 2012). In these communities, IFMSLP activities were piloted during phase I, alongside capacity building of frontline Department of Forestry staff. The IFMSLP was scaled up during phase II with the beneficiary-catchment areas expanded from 5km to 20km with respect to Reserve boundaries.

Communities received legal rights to manage and harvest forest products through Forest Management Plans negotiated with Malawi's Department of Forestry (Kamoto et al., 2023). Although the final total is disputed, over 200 Plans, one per community, were initially established by the end of phase I in 2009 (Olivier and Mwase, 2012). The majority of Plans were finalised at the end of phase II, in 2013 and 2014, ending a process that involved negotiation of the Plans, forest resource and livelihood assessments, and institution building (Remme et al., 2015). Block Management Committees and Village Natural Resource Management Committees were created for managing, respectively, Blocks and Village Forest Areas. To help finance the costs of running these new institutions, households were charged licence fees to access and withdraw forest resources, with exemptions made for poorer households (Kamoto et al., 2023). Institutional support, for enhancing communities' monitoring and enforcement capabilities, was provided as was financial and technical support for the establishment of Forest Based Enterprises tasked with income generation (Olivier and Mwase, 2012; Remme et al., 2015). Almost 400 Enterprises were established during phase I to increase the returns from resource extraction. These Enterprises supported and promoted a range of activities, either by commercialising pre-existing activities, such as the harvesting of fuelwood,

[16] Legal ownership rights were not transferred, although communities often felt a greater sense of ownership to customary land than land in Forest Reserves (Remme et al., 2015).

timber and non-timber forest products, e.g. mushroom production, or by establishing new activities, including tree nurseries and honey production. The IFMSLP also provided opportunities for wage labour via the construction and maintenance of firebreaks in forest areas.

Qualitative evidence suggests that the IFMSLP had variable effectiveness. Despite isolated success stories, about 70% of Enterprises became dormant between the end of phase I and start of phase II, reportedly due to inadequate access to markets and low levels of production (Remme et al., 2015). The performance of institutions tasked with management and exclusion also varied. For example, fees for supporting these institutions were often punitive and infrequently collected, with community members avoiding payment (Olivier and Mwase, 2012; Remme et al., 2015; Kamoto et al., 2023). Although this evidence is selective, it suggests that the IFMSLP likely had variable effects on well-being and rates of forest loss.

4 Data and Methodology

4.1 Data

Information on households' socioeconomic characteristics, food security, and agricultural and non-agricultural activities is drawn from the World Bank's Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA).[17] We use the Integrated Panel Household Surveys (IHPS) for Malawi across four survey rounds: 2010, 2013, 2016 and 2019. Via the tracking of both original and split-off households,[18] the sample, which comprised 1,619 households during the first survey round, grew to 3,178 households by the fourth round. Malawi's LSMS-ISA surveys are characterized by a low household attrition rate, around four percent in the 2013 and 2016 waves, and close to six percent in the 2019 wave (World Bank, 2019). Households were sampled and interviewed in 102 household enumeration areas (EA), roughly corresponding to village communities. We obtain GPS coordinates for all EA,[19] which we overlay with geo-spatial data on Malawi's Forest Reserves from the country's Forestry Department's website.

Forest data are sourced from the Global Forest Change dataset (Hansen et al., 2013),[20] specifi-

[17]The LSMS-ISA are nationally representative panel household surveys with a focus on agriculture, which have been established in eight sub-Saharan African countries.

[18]Following the first round of the Integrated Household Survey (IHS) conducted between March 2010 and March 2011, all interviewed households were tracked and, wherever possible, re-interviewed in subsequent survey rounds. In addition, split-off households and individuals, those who moved from their 2010/2011 location to establish and/or join new households, were also tracked and interviewed across waves, thereby expanding the panel sample in each survey round.

[19]To preserve confidentiality, the LSMS-ISA team randomly displaces household GPS coordinates within a predetermined range, referred to as a "location offset", of 0–2km in urban areas and 0–5km in rural areas, where the risk of disclosure is higher due to greater spatial dispersion of communities.(National Statistical Office of Malawi, 2012).

[20]The dataset provides information on global forest cover and change over the period 2000 to 2024 at a spatial resolution of approximately 30m per pixel at the equator. Forest is defined as vegetation that is taller than 5m in height, and forest loss as a "stand-replacement disturbance, or a change from a forest to non-forest state" (Hansen et al., 2013).

cally, the variables *Tree canopy cover for year 2000* (ranging from 0 to 100%) and *Year of gross forest cover loss event* (between 2000 and 2024). We adopt the FAO's definition of forests to characterize pixels as either forested or non-forested in the tree cover layer.[21] Thus, only pixels for which forest cover in 2000 was greater than 10% was kept in the tree cover layer, which were used as a mask layer for the tree loss data so that it only contains pixels that were characterized as forested in 2000. The rate of (gross) forest loss is calculated as the ratio of the count of pixels detected as forest loss in a given area (see below), and in the year prior to the survey year (e.g., 2015 for 2016), relative to the count of pixels that were reported as forested in 2000.

4.2 Construction of the treatment and control groups

Our treatment period is phase II, when, building on phase I, the IFMSLP was scaled up in all Impact Areas and the Forest Management Plans were finalised. A treated household is one residing in a community that was selected to participate in the IFMSLP during phase II. We first identify the Impact Areas [22] where the IFMSLP was implemented. Using the Forest Reserve polygons integrated with the geo-locations of the EA, we create 20km catchments around the Reserves within each Impact Area, corresponding to the maximum extent of the beneficiary-catchment area established during phase II. To differentiate between households who had enrolled in the IFMSLP in phase I and phase II from those who had enrolled in phase II only, for each Reserve we subtract the area within 5km of the Reserve borders thus excluding phase I treated EA. Households surveyed in EA located between 5km and 20km of treated Reserves are retained in our treatment group.

To construct our control group, we create similar 20km buffers around the Reserves that were not selected for inclusion in the IFMSLP from which we also subtract areas (and EA) located within 5km of the Reserve borders, so that the locations of the treated and non-treated households are as similar as possible. Next, we overlay our EA on to the Reserve polygons. This process is repeated for each survey year, taking care to remove polygons that overlap to ensure that all control EA are located a minimum of 20km from a treated Reserve. Likewise, treated EA are checked that they are located at least 20km from a control Reserve. In sum, treated EA are located 5-20km from a Reserve selected into the IFMSLP and at least 20km away from a control Reserve, while control EA are located 5-20km from a Reserve not included in the IFMSLP and at least 20km away from a treated Reserve. All Reserves included in our analysis are cross-checked with the World

[21] The FAO defines forests as "land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds *in situ*" (FRA, 2020).

[22] Note that we were unable to precisely locate two impact areas, Chawa (Proposed Forest Reserve) and the Masenjere Escarpment. These areas are neither included in the dataset retrieved from Malawi's Forestry Department'data platform nor listed in the World Database on Protected Areas (WDPA). As a result, we exclude from the analysis the districts in which these areas are presumed to be located, namely Kasungu District for Chawa and Chikhwawa District for the Masenjere Escarpment.

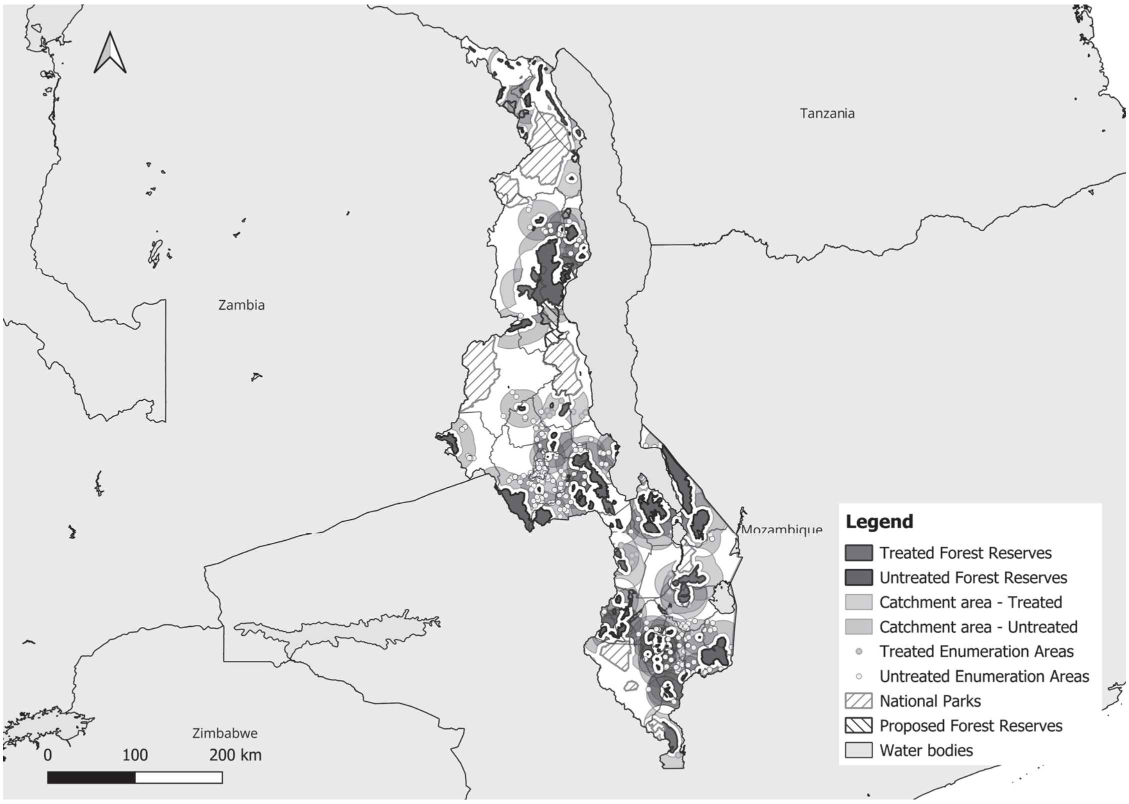

Figure 2: Location of treated and non-treated EAs

Notes: The map displays treated and untreated enumeration areas (EAs) included in the 2010–2016 and 2010–2019 samples, respectively. Catchment areas reflect the main sample configuration used in the analysis. Treated EAs are located between 5 and 20 km from the boundaries of a treated forest reserve (FR) and at least 20 km from the boundaries of an untreated FR. Conversely, untreated EAs are located between 5 and 20 km from the boundaries of an untreated FR and at least 20 km from the boundaries of a treated FR. To further avoid spatial overlap, catchment areas were also defined so as not to intersect with National Parks, accounting for an additional 5 km buffer around park boundaries.

Database on Protected areas (IUCN and UNEP-WCMC, 2020) for their status during the study period (see Appendix B). National Parks and proposed Reserves are excluded from the control group. Figure 2 shows the location of the Reserves included in our analysis, distinguishing between those that were part of the IFMSLP from those that were not, and the location of treated and non-treated EA within the 20km catchments. To facilitate identification, there are no overlaps between treated and untreated catchment areas.

4.3 Outcome measures

We adopt three different yet closely-related measures of household well-being: food security, assets, and a proxy for household incomes, non-food expenditures. First, forest product extraction, for own-consumption as well as for sale, suggests that a food security measure is a useful indicator of well-being in our context.[23] We adopt the Food Consumption Score (FCS), developed by the

[23] The consumption of a diverse range of food items and food groups is essential for the provision of key nutrients that support human health and well-being. While achieving dietary diversity remains a challenge in poorer countries, particularly among vulnerable communities whose diets are predominantly composed of starchy staples (Ruel and Cunningham, 2013), access to forest foods and other natural resources can play an important role in improving individual and household

World Food Programme (WFP) in 1996. The FCS captures the diversity and relative nutritional value of food groups consumed by a household in the previous seven days, as well as the frequency of consumption (World Food Programme, 2008). It is calculated by aggregating the consumption frequencies of eight different food groups and multiplying these frequencies by a standardized weight (see Appendix C). Second, we calculate the household's current asset value by summing the reported values associated with the durable goods owned by the household, such as tables, beds, televisions, air conditioners and refrigerators. Our measure is adjusted for inflation, expressed in logarithmic form, and in Malawian Kwacha (MWK). Third, we construct a measure of non-food expenditures, comprising all expenses incurred by households over the previous week on items, such as kerosene, cigarettes, candles, and transportation. This measure captures basic needs, e.g. energy and mobility, and is also expressed in real terms, in logarithmic form, and in MWK.

Rural households typically collect fuelwood and other forest products on foot. To minimise walking time, households gather forest resources as close to their dwellings as possible. How the IFMSLP might have affected forest loss rates via changes in resource collection behaviour is tested by following Edmonds (2002), who utilized data on the quantities of fuelwood collected by households to create a measure of resource extraction. In the absence of fuelwood quantity data, we construct a novel measure of forest loss using the reported travel time (in minutes) that household members required in 2010 to walk from their dwelling to their firewood collection site.[24] We calculate the average time spent walking, across all households, to be about 60 minutes. To translate this into a firewood collection range, we assume that walking 1km takes 10 minutes and, to account for GPS offsets, we add an additional 5km. This results in an 11km fuelwood collection range around every EA. Within this range, we then compute the percentage forest loss in the year prior to the survey rounds, that is, in 2009, 2015 and 2018.[25] In our main results, we estimate the model using the full sample in order to avoid an excessive loss of observations. However, because our measure relies on fuelwood collection time reported in 2010, we also present results from a restricted sample in which households are required to have remained within 10km of their original 2010 location in subsequent survey rounds. We adopt a measure for all forest and distinguish between forest loss in Forest Reserves and in customary land.[26] Finally, we check our results using individual household collection times reported in 2010, dropping missing values.

nutritional status.

[24]Due to this measure in subsequent survey years being likely endogenous to outcomes, we retain the 2010 values for calculating forest loss rates in 2016 and 2019.

[25]Many questions in the survey are based on household activities conducted 12 months prior to the questionnaire.

[26]Note that although our data reveal neither the precise locations of the Forest Reserve Blocks nor the Village Forest Areas in the Impact Areas, it is documented that both, particularly the latter, are typically located within walking distance of villages (Olivier and Mwase, 2012; Remme et al., 2015; Kamoto et al., 2023).

4.4 Empirical Strategy

A causal relationship is inferred between phase II of the IFMSLP and its impacts on household wellbeing and forest loss rates. Observations from the 2010 household survey are utilised as baselines to estimate the impacts of the IFMSLP in 2016 and 2019, respectively, two and five years after the end of phase II in 2014. Some households changed locations between 2010 and 2016/2019, leading some to either switch in or out of the treated areas and hence, change their treatment status between the baseline and subsequent survey rounds.[27] These households are removed from the sample. In the 2010-2016 sample, there are 304 treated and 1,844 control households while the 2010-2019 sample has 372 treated and 2,228 control households.[28]

The emphasis of Malawi's forest policy on improving livelihoods (Section 3) suggests possible bias in terms of the choice of Forest Reserves for selection into the IFMSLP. A comparison of our outcome measures calculated from the unmatched treated and control groups reveals that the FCS, asset values and non-food expenditures are higher in our control group than our treated group, in both the 2010-16 and 2010-19 samples (Appendix D). For the latter two measures, these differences are statistically significant. Forest loss rates are higher in the treated vis-a-vis the control group.

We estimate Rubin (1974)'s causal model, where T is denoted as the treatment variable, such that $T = 1$ if households reside within the phase II beneficiary-catchment area of the IFMSLP, and 0 otherwise. Outcomes for household i are denoted Y_i^1 when $T = 1$, and Y_i^0 when $T = 0$. We therefore do not observe Y_i^1 for our control group, and similarly, we do not observe Y_i^0 for our treated group. The average treatment effect on the treated (ATT) is defined in the standard way:

$$\Delta^{ATT} = E(Y_i^1 - Y_i^0|T = 1) = E(Y_i^1|X, T = 1) - E(Y_i^0|X, T = 1) \qquad (1)$$

where X represents the set of households' observed characteristics. The ATT represents the differences in average outcomes between households resident in the treatment area during the implementation of phase II, and those in the treatment area before implementation, which cannot be directly computed. It is hence necessary to construct a counterfactual group. To address the potential for selection bias and account for differences in unobservable characteristics between our treated and

[27]Household members leaving the baseline household to form or join a new household in the following year(s) may no longer be located in a treated area while continuing to be associated with the identification number of their original household.

[28]Because the LSMS-ISA survey design explicitly tracks split-off households, and due to additional household attrition over time, arising from migration, mortality, tracking loss, and related factors, achieving identical household samples for the 2010–2016 and 2010–2019 panels is challenging. Even when split-off households are excluded, differences in sample composition persist across periods.

control groups, we adopt a simple two-period differences-in-differences (DiD) framework:

$$Y_{it} = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Post_t + \beta_3 * (Treatment * Post)_{it} + \delta_i + \mu_{it} \tag{2}$$

where Y_{it} is the outcome for household i at time t, which is either the FCS, the value of durable goods (log, real terms, MWK), value of non-food expenditures in the past week (log, real terms, MWK), or forest loss within the average walking range for collecting fuelwood in the EA of household i, as calculated in 2010; δ_i represents the time-invariant household fixed effect; and μ_{it} is the error term. The coefficient β_3 captures the treatment effect, which is equivalent to the differences between our baseline period and a post-treatment period, and our two groups of households:

$$\beta_3 = [E(Y_i|X, T = 1, t = 1) - E(Y_i|X, T = 1, t = 0)] - [E(Y_i|X, T = 0, t = 1) - E(Y_i|X, T = 0, t = 0)] \tag{3}$$

where t represents the period such that $t = 0$ is the pre-treatment period (corresponding to the year 2010), and $t = 1$ is the post-treatment period (either 2016 or 2019). In all estimations, the standard errors are clustered at the EA level.

The DiD framework relies on the parallel-trends assumption, in which households resident in the Impact Areas, in the absence of treatment, would have followed the same trends with regard to well-being and tree cover as those unaffected by the IFMSLP (see Appendix E). To compare treated and non-treated households while minimising bias resulting from differences in the characteristics between both groups, we combine our DiD model with Propensity Score Matching (PSM) (Heckman et al., 1997; Dehejia and Wahba, 2002).[29] We adopt Kernel matching (with a bandwidth of 0.01), a non-parametric matching estimator that constructs the counterfactual by using the weighted averages of all untreated households (Caliendo and Kopeinig, 2008). Matching variables include: household size (count); livestock ownership (1=yes); value of durable assets (log, real terms, MWK); non-food expenditures in the past week (log, real terms, MWK); distance of households' EA to the closest major population center (km); elevation (m); average forest cover in an area of 10km around EA (%), and; distance of households' EA to the closest major lake (Lake Niassa, Chilwa, or Malombe). Matching is conducted at baseline, in 2010. Results of the balancing tests show that PSM effectively narrowed the differences between the treated and control groups (Appendix F). After matching, in contrast to pre-matching trends, the treated group had higher well-being levels than the control group in 2010 (Appendix E).

Lacking pre-treatment trend data, we first check our results by re-running the DiD estimator

[29] PSM computes, via a logit or probit model, the probability of being in the treatment group based on a set of observable characteristics. We adopt a probit model to estimate the propensity score and note that a logit model yields similar results.

using 2013 outcomes as a kind of placebo test, anticipating null effects. Although phase II began in 2012, forest rights were transferred to most if not all communities in 2013 and 2014 (Remme et al., 2015). Next, we estimate the average treatment effect on the treated after conditioning on covariates via application of the doubly-robust estimator (Sant'Anna & Zhao, 2020) to our data. To check whether background structural economic changes in the EA are influencing outcomes, we include two new variables: the % agricultural land within a 1km radius of the EA and the presence of a health clinic (*Chipatala*) in the community.

We next check the validity of our treatment areas, assumed to be located between 5 and 20km from Forest Reserve boundaries (Olivier and Mwase, 2012), by first including treated and control EA located within 0-5km of Forest Reserves (Phase I households). The expectation is a weakening of our results due to the inclusion of households first treated in phase I. We also create a 'never treated' sample of households in Impact Areas, located 25 to 45km away from Reserve boundaries, again anticipating a null result. The sensitivity of our results due to the location offset is assessed by adjusting the treatment area in two ways so that, respectively, only EA within 5 to 10km and 5 to 25km of Reserve boundaries, are included in both treated and control groups; treated households are also located at least 25km away from any control Reserve while untreated households are located at least 25km away from any treated Reserve (instead of 20km). Related to the choice of treatment areas is the potential for possible spatial spillovers. First, we create more distance between treated and control EA by including the restriction that treated and control EA are at least 20km away from one another. Second, to create distance between phase I and phase II households we restrict the treated and control EA to within 10-20km away from Reserves instead of 5-20km.

To ensure that our results are not biased by implementation of a follow-up policy to the IFMSLP, the PERFORM project, we remove from our sample the three districts in which this project was implemented between 2014 and 2019,[30] and re-run the DiD for 2019 outcomes.

We explore whether the composition of our household sample biases our result by first estimating the unweighted DiD and after reinstating weights, removing households resident in Lilongwe district from the control group. That Malawi's capital city is located in this district could bias our results downwards if access to the capital provides, e.g. labour opportunities, unavailable elsewhere.

The sensitivity of our results due to our choice of outcome measures is examined by first, removing energy expenditures from our measure of non-food expenditures and second, by assuming a smaller range for fuelwood collection at the EA scale (6km) and calculating forest loss rates within

[30] After the conclusion of the IFMSLP in 2014, the Protecting Ecosystems and Restoring Forests in Malawi (PERFORM) project was implemented in the Forest Reserves of Perekezi, Ntchisi, and Liwonde in the Mzimba, Ntchisi, Machinga districts, respectively, between 2014 and 2019. The purpose of PERFORM was to 'consolidate and improve the legacy of the IFMSLP' (Kamoto et al., 2023).

this range. Relatedly, we check our outcomes are driven by the IFMSLP and not some unobserved event, specifically, a weather shock (drought or flood) in 2015 and/or 2016. We re-run our DiD estimator using values of the Standardized Precipitation Evapotranspiration Index (SPEI) as outcomes instead of our policy outcomes, anticipating little or no effect on the outcome. We consider four alternative outcomes based on the SPEI data: (i) a continuous SPEI measure at periods SPEI_t and SPEI_{t-1} relative to the survey year, and; (ii) a binary shock indicator, similarly defined at periods SPEI_t and SPEI_{t-1} relative to the survey year.

Finally, we check that our choice of matching is not driving results by first, varying the Kernel matching bandwidth (0.001, 0.05, 0.1) and second, by applying alternative matching algorithms to our data, including one-to-one matching, nearest neighbour matching and radius matching.

5 Results: policy outcomes

Table 1 shows our results for the impacts of the IFMSLP on households' well-being, as measured by food security, the value of assets and non-food expenditures, as well as forest loss rates.

Table 1: Treatment effect on the policy's outcomes

	2016				**2019**			
Dependent variables	FCS	Assets	Exp.	Forest loss	FCS	Assets	Exp.	Forest loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	7.244***	0.240	0.318	-0.00863	5.569*	0.317	0.131	-0.0151
	(2.671)	(0.301)	(0.343)	(0.0380)	(2.904)	(0.310)	(0.331)	(0.0418)
Post treatment	-3.080*	0.296**	0.0171	0.113**	-1.489	0.486***	-0.0608	0.146***
	(1.733)	(0.142)	(0.166)	(0.0521)	(1.658)	(0.125)	(0.180)	(0.0474)
Treatment X Post	**-8.333****	-0.302	**-0.834****	-0.0237	-2.805	-0.529	0.109	0.0513
	(3.602)	(0.285)	(0.399)	(0.0611)	(2.001)	(0.332)	(0.350)	(0.113)
Observations	1,150	1,116	1,085	1,150	1,490	1,418	1,407	1,490
R-squared	0.070	0.005	0.032	0.070	0.027	0.011	0.003	0.137

Notes: DiD estimation with weights from Kernel matching. Robust standard errors in parentheses clustered at the EA level. *** p<0.01, ** p<0.05, * p<0.1.

After the end of phase II in 2014, households living in the Impact Areas experienced falls in their FCS and non-food expenditures. In 2016, treatment reduced households' FCS by 8.333 units, corresponding to approximately 17% of the sample mean of the FCS (48.3),[31] and about 7.4% of its maximum possible value (112), at a 5% level of statistical significance (Table 1, column 1). The magnitude of the fall in the FCS is also equivalent to the absence of main staples in a

[31] Mean of the FCS using the 2010-2016 sample.

household's diet for about four days. The coefficient on non-food expenditures, -0.834, is also statistically significant at the 5% level (column 3), corresponding to a 56.6% decline[32] relative to the control group. Although again negative, coefficients for the value of assets (column 2) and the rate of forest loss (column 4) are not statistically significant. The negative sign on the forest loss coefficient implies a reduction in the forest loss rate. Similar results are estimated when we consider forest loss rates in Forest Reserves and customary forest areas separately, and when the sample is restricted to households reporting fuelwood collection time in 2010 (Appendix G).

Five years after the end of the programme, the treatment is again associated with a decrease in the FCS, this time by 2.805 units (Table 1, column 5), an impact that is not statistically significant. Although now positive, the impact on expenditures is also not statistically significant (column 7). With respect to forest loss, while not statistically significant the positive coefficient indicates a shift to more rather than less forest loss compared to the 2016 estimates (column 8). Overall, the IFMSLP appears to have had no impact on wellbeing or forest loss rates in 2019.

Summarised in Figure 3 and 4 are the results from the robustness checks on the key changes observed in Table 1, that is, with respect to the impacts on the FCS and non-food expenditures in 2016. We distinguish these checks according to whether they anticipate results quantitatively and qualitatively similar to those in Table 1 (top two panels of Figure 3), or null results (bottom two panels of Figure 3, and Figure 4). Results summaries for the other outcome variables, and for the 2019 results, are shown in Appendix H, while the full results for all checks are in Appendix I. Overall, this battery of checks offer reassurance regarding the consistency and robustness of our results in Table 1, particularly for the FCS. The coefficient for the FCS in 2016 ranges between -6.238 and -12.02 while that for non-food expenditures ranges between -0.429 and -1.573.

Notable differences between our main results and the checks include the results of the application of the doubly-robust estimator, which suggest statistically significant negative co-efficients for the FCS and assets in 2019. Inclusion of community-level variables as additional matching variables reduces statistical significance on the coefficient for non-food expenditures in 2016, while the negative coefficient on the FCS is statistically significant in 2019. Similar results are obtained from the sensitivity checks related to treatment areas due to the location offset. When we adopt nearest neighbour matching, the coefficient for the FCS loses some statistical significance while that for non-food expenditures loses statistical significance altogether.

In contrast to the results in Table 1, rates of forest loss are positive and statistically significant, implying higher rates of loss, when restricting the household sample to within 10-20km of Reserve

[32] $100 \times (e^{-0.834} - 1)$

boundaries. Also in contrast to our main results, we find a declining and statistically significant rate of forest loss in 2019 when removing the PERFORM districts, implying that districts not treated by further policy intervention experience better forest outcomes than those that were treated. While suggestive of an interesting avenue for further research, these checks reveal that our forest loss results are less consistent than those for well-being. Our forest loss estimates possibly reflect the proxy nature of this measure and the fact that many of the extractive activities undertaken by households, such as fuelwood collection, do not typically involve forest clearance.

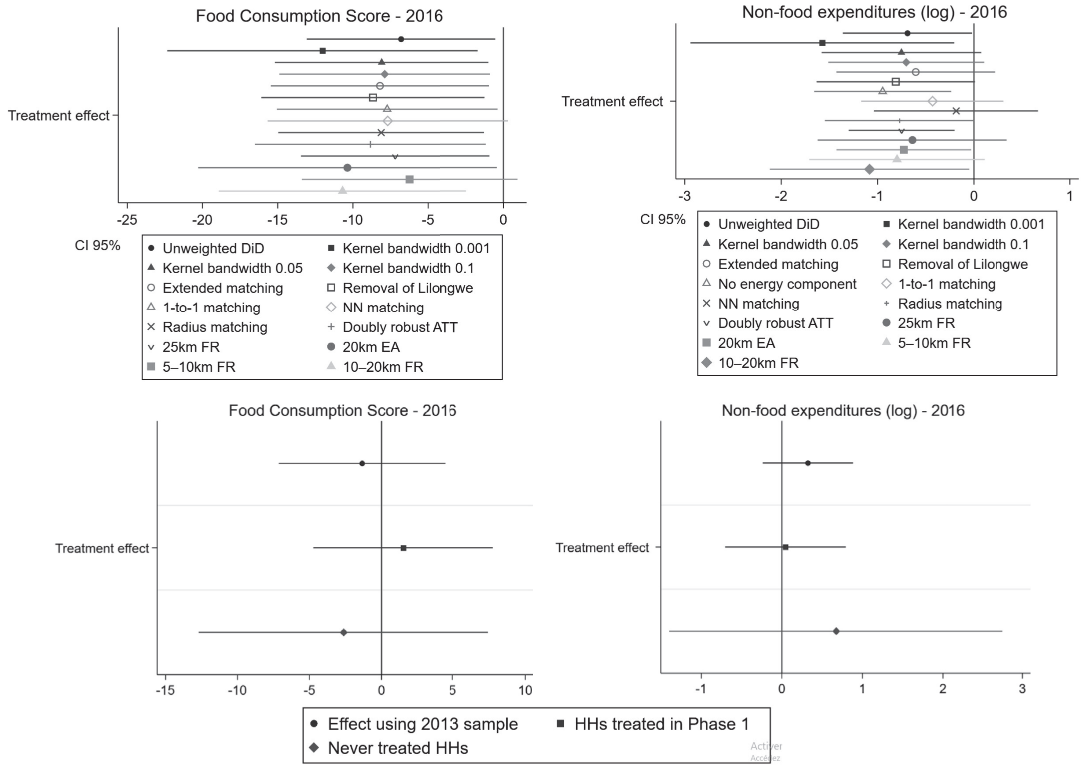

Figure 3: Robustness checks - overview for the FCS and non-food expenditures (2016)

Notes: The top two panels present robustness checks for the Food Consumption Score (FCS) and non-food expenditures, respectively, under specifications that are expected to yield estimates consistent with our main results. Specifically, we assess the sensitivity of our findings to a range of alternative specifications, including an unweighted difference-in-differences estimator; alternative matching strategies and matching specifications; and the exclusion of the capital city and its surrounding areas. In addition, for the non-food expenditure outcome, we consider an alternative outcome definition by excluding energy-related purchases from non-food expenditures. We further examine robustness to the use of a doubly robust estimator; to alternative definitions of treatment and control groups based on distance to Forest Reserve (FR) boundaries, including treated households located 5–25 km, 5–10 km, or 10–20 km from treated FR boundaries and at least 25 km or 10 km from untreated FR boundaries, with symmetric definitions for untreated households, and to spatial separation between Enumeration Areas (EAs), by restricting the sample to cases in which EAs from different groups are located at least 20 km apart. The bottom two panels report robustness checks for the FCS and non-food expenditures under specifications in which no significant treatment effects are expected. These include tests of the treatment's effect on the 2013 sample, on households located outside the program's catchment areas, and on households treated during the first phase of the IFMSLP. Detailed descriptions of these robustness checks are provided in Appendix H.

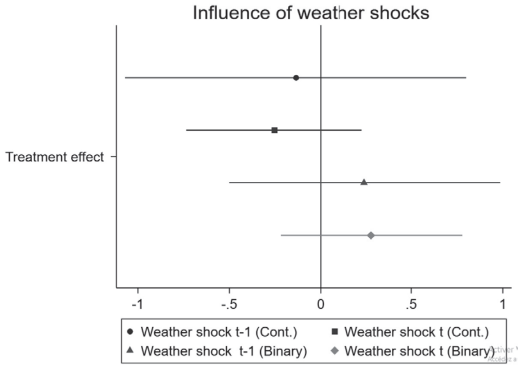

Figure 4: Robustness checks - influence of a weather shock on DiD estimates (2016)

Notes: The figure presents the results of the tests used to assess whether weather shocks influence the effect of the treatment. As detailed in Appendix I.8, these tests rely on the SPEI as the main outcome, in order to examine whether the treatment effects observed on our primary outcomes are associated with the occurrence of weather shocks. Specifically, we test the effect of the treatment on the SPEI (in continuous form) in periods t and t_{-1}, as well as the effect of the treatment using a binary indicator equal to 1 when the SPEI exceeds an absolute value of 1, again in periods t and t_{-1}.

6 The role of baseline institutional strength and resource dependence

The IFMSLP was responsible for a decline in households' well-being, in 2016, and had no impact on forest loss rates. Returning to the theory in Section 2, unchanged forest loss rates imply, in the baseline, either strong community capacity to regulate labour to extraction and zero (or negative) forest loss rates, or weak capacity to regulate extraction behaviour and positive forest loss rates. In either case, our estimated unchanged forest loss rates in Table 1 suggest that investments to improve capacity had little impact in our study period. From the data, we note positive and rising rates of forest loss between 2010 and 2019 (Appendix E). In the 10 years prior to 2010, rates of forest loss were consistently positive, suggestive of open access and weak community capacity to regulate labour to extraction prior to phase II, which we explore further below.

Again returning to Section 2, securing access and withdrawal rights might have incentivised more labour to extraction. But if regulation of members' labour, and the labour of non-members, remained weak, while investments to improve resource production failed, then the average returns to extraction are likely to have declined thus contributing to the observed fall in well-being in 2016.[33] Although we do not observe the average returns to extraction, a decline is expected to affect mostly those with limited *ex ante* outside options: unskilled members dependent on resource

[33]We note that well-being could decline when management capacity is improved (reducing members' labour to extraction) while the capacity to exclude remains ineffective (increasing non-members' labour to extraction), also implying a continuation of open access and unchanged forest loss rates (Section 2). Case study evidence suggests that community members spent more time collecting forest resources in Impact Areas (e.g. Kamoto et al., 2023). When applying DiD to data on household labour assigned to fuelwood collection, we also find an increase, rather than a decline, in labour, although this result is not statistically significant (Appendix J).

extraction for their incomes and livelihoods. The idea here is that a rational household facing lower returns to labour when extracting resources would switch to their outside option yet when these are either unavailable or inaccessible they continue extracting resources even if it is sub-optimal to do so (Delacote, 2009; Barbier, 2010; Barbier and Hochard, 2019).

6.1 Communal forest claims

We first examine the evidence for the relative strength of the community's capacity to regulate labour to extraction in 2010. The IFMSLP was implemented in Forest Reserves and customary areas and although we do not observe whether households attempted to harvest forest products in the former prior to phase II, they were defined *de jure* as mixed use. Thus, limited resource extraction, mainly forest and non-forest products, by communities was permitted. The IFMSLP attempted to clarify and formalise the mixed use status of Reserves as *de jure* access and withdrawal rights in the Forest Management Plans. Communities likely had stronger *de facto* rights in their customary territories than in the Reserves, rights that were also formalised in the Plans.

Our dataset includes the responses given by community leaders to a community survey. From the 2010 data on resource claims and institutions, the responses to a question on the existence of a community forest claim has a response rate sufficient for our analysis.[34] These responses proxy for the prior existence of community capacity to regulate labour, both of members and non-members, to extraction. We assume that a community not claiming forest in 2010 had little or no capacity, and was more likely to benefit from the IFMSLP's institution-building efforts than a community with a forest claim. Equations 2 and 3 are re-estimated using sub-samples split according to whether a household resided in a community with a forest claim. Figure 5 and 6 show that forest loss rates did not change regardless of whether there was a prior forest claim, implying ineffective institution-building efforts. Households residing in a community with no prior claim are thus expected to be subject to little or no effective community regulation when allocating more labour into resource extraction and hence, are more likely to experience a decline in well-being in contrast to households in communities with a prior claim. Results in Figure 5 support this hypothesis: the negative effects on food security and non-food expenditures in 2016 occurred among households resident in communities with no prior claim. We note wide 95% CI, likely due to the crude nature of the proxy for baseline institutional strength, including the possibility that it masks heterogeneity among households in a given community.

[34]Specifically, the question asks whether the community possesses any communal resources. Among the response options is 'communal forest'. Accordingly, we interpret that communities reporting ownership of a communal forest in 2010 are considered to have had a forest claim in that year, whereas those that did not report ownership of a communal forest are regarded as having had no forest claim in 2010.

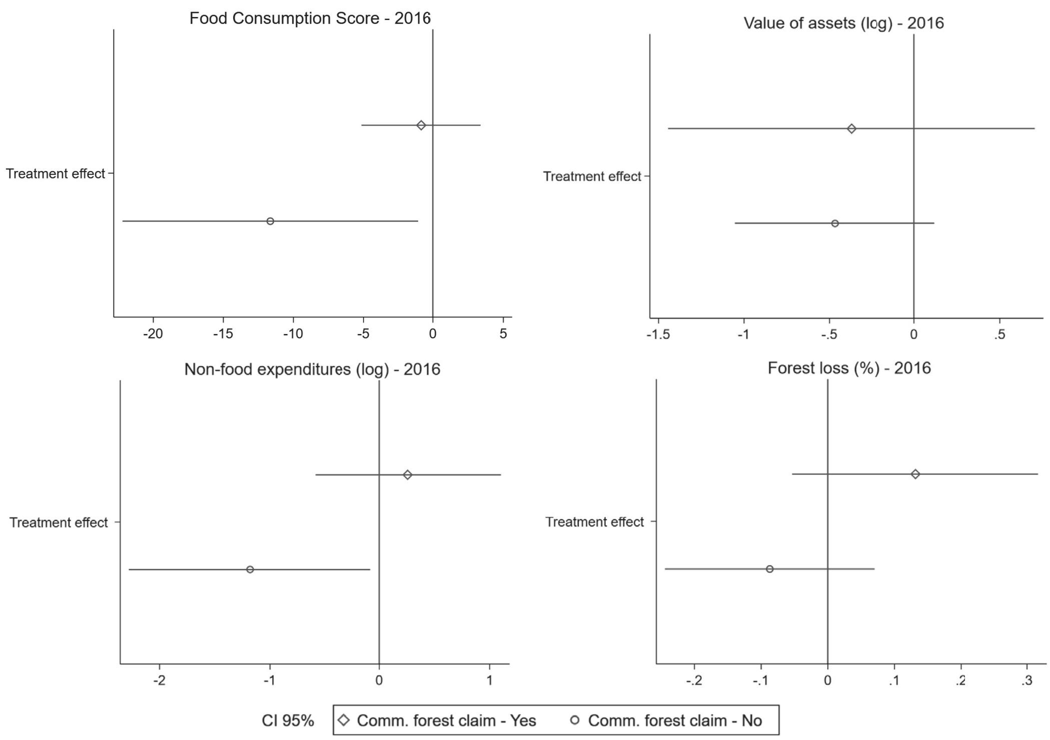

Figure 5: Heterogeneous impacts based on communal forest claims - 2016

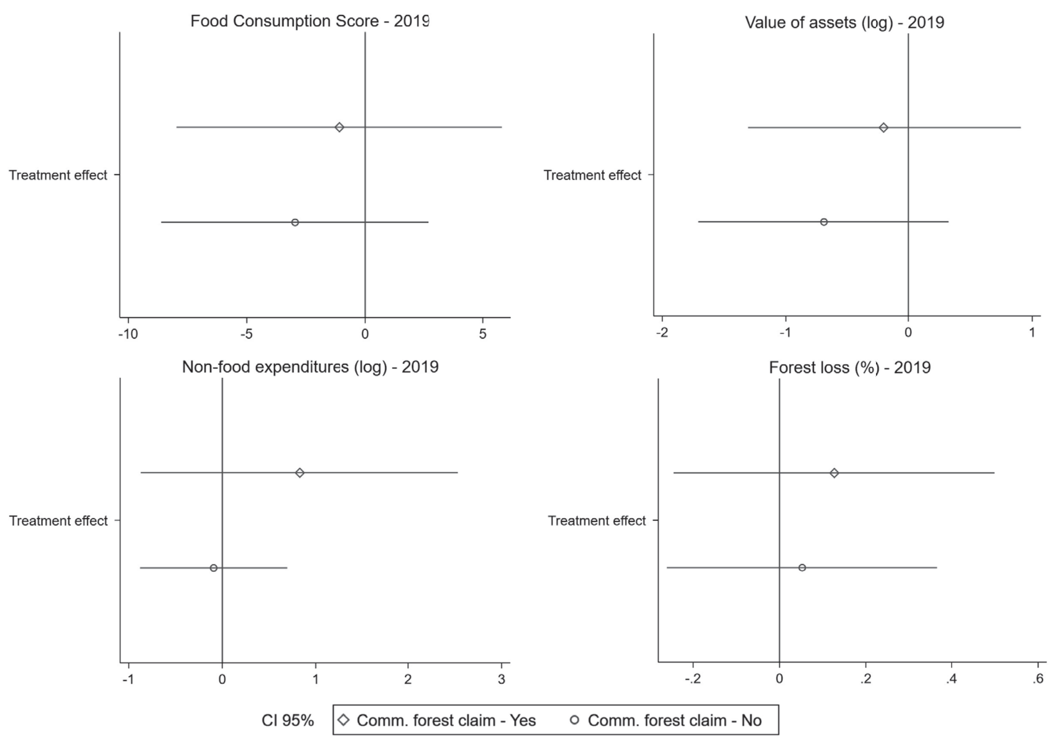

Figure 6: Heterogeneous impacts based on communal forest claims - 2019

6.2 The household's allocation of labour

We next investigate how the IFMSLP affected well-being and forest outcomes conditional on the extent to which members within the same household engaged in either (subsistence) agriculture, non-agriculture work, *ganyu*, wage labour, or fuelwood collection, in 2010. In the data, these measures are expressed in terms of the number of hours that household members engaged with each activity in the previous week except for fuelwood collection, which is based on the number of hours spent collecting the day prior to the survey. We create two groups of households, and re-estimate Equations 2 and 3. In the first, unskilled households engaged in fuelwood collection and/or subsistence agriculture in 2010,[35] and with zero hours collectively allocated to *ganyu*, wage and non-agricultural labour. Mid-skilled or skilled households in the second group primarily engaged in *ganyu*, wage or non-agricultural labour, and potentially, to some extent, fuelwood collection and/or subsistence agriculture.

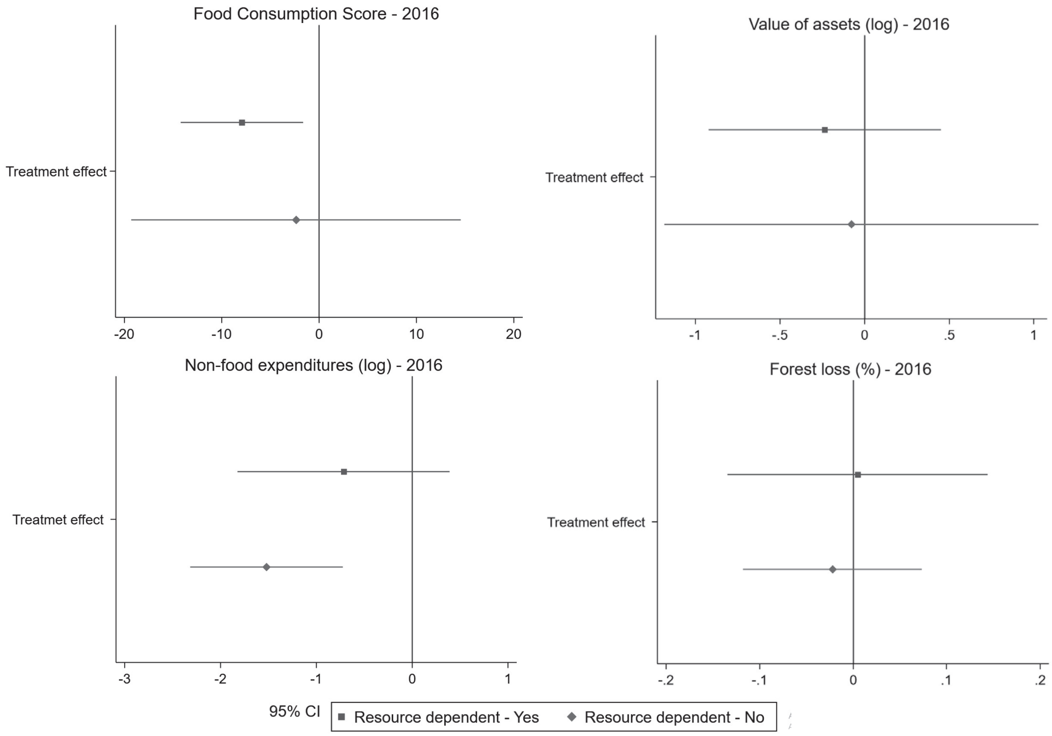

Figure 7: Heterogeneous impacts based on the household's labour allocation - 2016

[35]The 2010 survey has a question on farming activities that was augmented in the following survey waves with two additional questions, one on livestock activities and one on fishing. Thus, under the assumption that the 2010 survey question on farming activities implicitly includes time spent on livestock and fishing, we combine the time spent on all of these activities and collectively label these 'agricultural labour'.

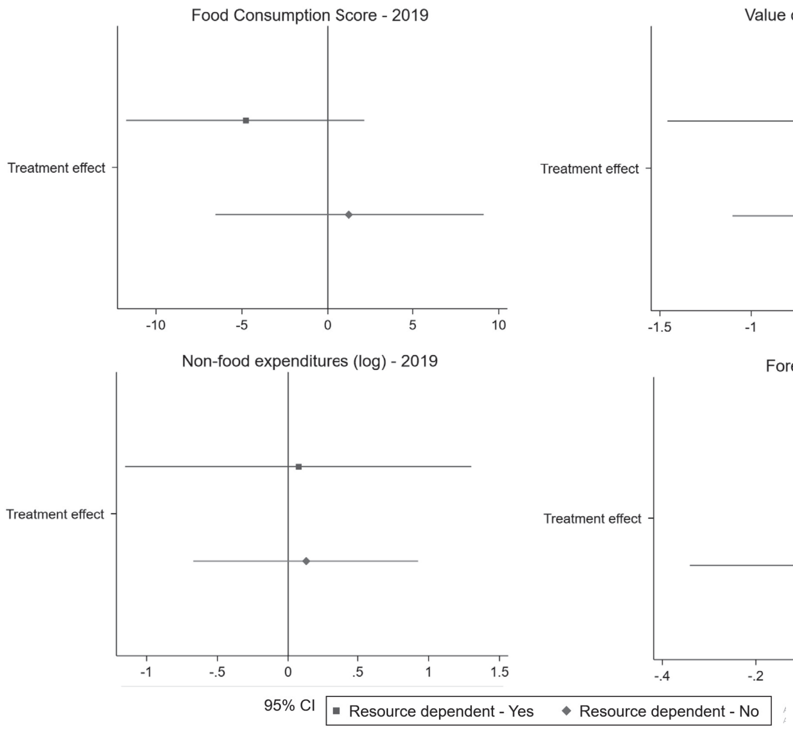

Figure 8: Heterogeneous impacts based on labour the household's labour allocation - 2019

The fall in food security in 2016 is concentrated among households who were dependent on either fuelwood or subsistence agriculture for their incomes and livelihoods (Figure 7). This impact on well-being concerns peoples' vital needs, i.e. nutrition. By contrast, the fall in non-food expenditures in 2016, found among households primarily engaged in either *ganyu*, wage labor, or non-agriculture work, is related to less- or non-vital needs. We speculate that the difference between the two groups might be due to the availability of cash income with those more dependent on resources likely to earn less cash than those with off-farm labour opportunities. Indeed, non-food expenditures among the less dependent households are, on average, higher than more dependent ones in 2010 (Appendix K). However, as in Table 1, effects are not statistically significant in 2019 (Figure 8). These results suggest that, in the short-run, myopic households increased their labour to extraction and, upon realising a loss in well-being, switched their labour to their outside options where available. This switch is more likely among households with access either *ganyu*, wage labor, or non-agriculture work; indeed, we note a positive point estimate for the less resource-dependent households with respect to non-food expenditures in Figure 8. With the caveat that we use different samples to estimate the 2016 and 2019 coefficients, this result is suggestive of a stronger adjustment capacity in the long run related to better outside options. By contrast, the point estimate of resource-dependent households with respect to the FCS, although also not statistically significant, is also negative in 2019.

7 Discussion and Conclusion

Since the 1990s, the total global area legally owned or designated as common property has grown, and continues to grow; projections suggest a doubling of the area recognised between 2015-2020 (Rights and Resources Initiative, 2023).[36] Such growth is projected to take place in settings with competing land pressures, including ongoing efforts to expand area-based conservation policies, for example, to meet the targets of the Kunming-Montreal Global Biodiversity Framework (UNEP, 2022). As practitioners and policy makers debate the conservation and poverty-reduction potential of efforts to secure the commons, the empirical evidence to date suggests mixed outcomes. To better understand these outcomes, we examined the institutional conditions under which securing the commons might conserve resources while improving well-being.

We first developed a simple theoretical framework in which securing the commons incentivises external investments in the community's capacity to regulate labour to extraction, and in resource production. Positive conservation and well-being outcomes are most likely in a relatively narrowly-defined scenario, that is, when all investments are effective. Under this scenario, a measurably impactful effort to secure the commons materialises when the community's capacity to regulate labour to extraction is already weak and where there is a high degree of resource dependence among members. From these baselines, reductions in resource degradation rates and changes in well-being should be observable. Our model has the benefit of comprising three separate components, with exclusion, management and access/withdrawal rights considered independently. Although we demonstrated how these components are linked in the context of a generic policy to influence all three components, our model can be easily adapted to other policies, e.g. land titling, that have only one or two components. Thus, our theory has external validity beyond policies like the IFMSLP. It also has external validity beyond forest commons, although we acknowledge that our model considers the commons as a single resource, neglecting the fact that a range of resources are typically extracted from forest commons for different consumptive and productive needs.

Critical to model outcomes are changes to the average returns to extraction, which we do not observe in our data. Yet, data for aggregate resource production and labour to extraction allocated by members and non-members could be collected in simpler settings where data might be more readily available, for example, in a given fishery. In forest commons settings, most empirical research, whether on land titling or community-based interventions, focuses either on conservation or well-being outcomes, and not both, typically finding either no, or a positive, change in outcomes.

[36] At least 11.4 percent of all land was legally controlled as common property across 73 surveyed countries (withdrawal, access, management, exclusion rights), in 2020. More limited designation rights are recognized in 7.2 percent of land. Implementation of existing legal frameworks could double the total area legally owned by, or designated for, communities.

Starting with the former, contrary to case study evidence suggesting a decline in forest resources due to increased extraction in Impact Areas (see, e.g. Kamoto et al., 2023), we found no change in forest loss rates, in 2016 and 2019. Instead, our results are consistent with a lack of impacts reported from land titling schemes implemented in, e.g. Brazil (BenYishay et al., 2017), Ecuador (Buntaine et al., 2015) and Indonesia (Kraus et al., 2021).

Theory suggests that unchanging forest loss rates was due to a weak or non-existent community capacity to regulate labour in the baseline, implying open access, followed by ineffective efforts to improve capacity, implying continued open access. Baseline trends of positive forest loss rates in Impact Areas are indeed suggestive of open access (Appendix E). Our results in Figure 5 and 6 suggest no difference in forest loss rates conditional on the existence of a communal forest claim, although this is unsurprising: why would we expect changes in forest loss rates if communities already had sufficient capacity to regulate labour to extraction? In such a setting, efforts to improve capacity would be expected to have little or no impact while limited baseline capacity, for example, to support *de facto* management rights (Hajjar et al., 2021), provides scope for a positive change in outcomes. We note that our crude measure of community capacity likely masks variation and that even with a forest claim, there might still be scope for improving capacity. Regardless, we stress the importance of strengthening the community's capacity to enforce both management and exclusion rights to effect positive change in resource outcomes, for otherwise the incentives to free-ride in the commons remain. That the community's capacity to regulate labour to extraction remained insufficient to change forest loss rates is perhaps to be expected given the limited timeframe of our study. Effective institution building takes time, as evidenced by Oldekop et al. (2019), who found that the estimated reduced deforestation impacts of community forest management in Nepal were greater where communities were subject to longer-term investments.

That time is needed for policies to be effective raises the question of the durability of efforts to secure the commons, specifically, the durability of property rights after they have been transferred or formalised. This point applies to well-being as well as resource outcomes. Given the incidence and extent of rural poverty in Malawi, our most striking result is an estimated decline in well-being, specifically large falls in the FCS and non-food expenditures, in 2016. The latter estimate reflects a proportional change in non-food expenditures relative to the control group; given relatively low baseline levels, a large proportional response is arguably plausible in our context. For the 2019 sample, we estimated null effects, results that are consistent with Pailler et al. (2015) who found that the benefits from community-based natural resource management appeared to increase with longer periods of implementation in Tanzania. In our case, the differences between 2016 and 2019 could be due to differing samples but might also, in line with our theory, reflect myopic behaviour in 2016 that adjusted in 2019, particularly among households with better outside options. The fall in the FCS and non-food expenditures in 2016 also indicates that not only was regulation on labour to extraction ineffective but also that efforts to boost resource production, via the Forest Based Enterprises, failed, potentially leading to a fall in the average return to extraction in the commons.

In many Enterprises, the emphasis was on the commercialisation and sale of fuelwood and non-timber forest products (Kamoto et al., 2023). Yet, profitability was reportedly low, exacerbated by the requirement that resource users pay licence fees to help pay for the running of new community institutions. The abandonment of groups set up for commercial resource production thus possibly contributed to the poor functioning of the new institutions as well as to the high rate of failure among Enterprises. This failure to raise the returns from resource extraction helps explain the short-term decline in well-being among resource-dependent households. As such, our results support the view that although resource dependence and subsistence can prevent further poverty, efforts to raise the returns from non-subsistence extraction in challenging institutional settings are unlikely to reduce poverty (Angelsen & Wunder, 2003). Thus, efforts to secure the commons should pay special attention to the well-being of beneficiaries who are likely to continue to be exposed to other institutional constraints, as demonstrated, for example, in Paraguay where credit-constrained smallholders were found to benefit the least from land reforms (Carter & Olinto, 2003).

Assets, and the growing of assets, are critical in poverty alleviation efforts, particularly with respect to the identification, measurement and breaking of structural poverty traps, defined as self-reinforcing cycles of poverty (Jalan and Ravallion, 2002; Barrett et al., 2011; Kraay and McKenzie, 2014; Barrett et al., 2016). Although the IFMSLP had a negative effect on assets in 2016, an effect that persisted among resource-dependent households in 2019 (Figure 7 and 8), these impacts were not statistically significant. Thus, there is no evidence of households falling into a poverty trap due to the IFMSLP, in line with research by Walelign et al. (2021) who found that reliance on so-called 'environmental income' in Nepal did not create poverty traps.

In conclusion, we argue that there are limits on the extent to which policies that emphasise support to resource extraction and the generation of environmental income can improve well-being and conserve resources. Our results suggest that, five years after the end of the IFMSLP, the policy had no impact and failed to meet its objectives. Yet, we acknowledge that natural resources do make important contributions to livelihoods, specifically as a source of products for own consumption (subsistence). Our theoretical and empirical insights could be used to target those communities and households who are most likely to benefit as well as those most vulnerable to policy failure, that is, to ensure a policy of do 'no harm'. Securing the commons for the benefit of local populations and ecosystems is both challenging and complex. Different channels through which securing the commons is facilitated must be considered, and the local context, characterised by the extent of external threats and market access, also plays a critical role in shaping outcomes, implying that there is no one-size-fits-all approach to making such interventions effective.

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Appendices

A A model of common-pool resource extraction

A.1 Labour allocation and groups of community members

Consider a community, represented as a continuum of community members $i \in [0,1]$, who allocate a share l_i of their labour to common-pool resource extraction and a share $(1-l_i)$ to an outside option. We introduce two *de facto* institutional variables that control the extent of labour allocated to resource extraction in the commons.

First, the strength of a community's *de facto* exclusion rights reflect the community's capacity to restrict possible trespassing and resource appropriation by people from outside the community. L_e is the amount of labour allocated to extraction by non-members. Lower (higher) L_e means higher (lower) capacity to exclude non-members from extraction.

Second, the strength of a community's *de facto* management rights reflects the community's capacity to restrict the amount of labour allocated to extraction by members (considering also that these limitations are respected): $l_i \leq \overline{l_i}$. Total labour allocated to extraction by members is thus also limited: $L_i = \int_0^1 l_i d_i \leq \overline{L_i} = \int_0^1 \overline{l_i} d_i$. Lower (higher) $\overline{l_i}$ represents higher (lower) capacity to constrain over-extraction by members. For $\overline{l_i} = 1$, there is no effective limit on extraction by members.

Combining both lower (higher) L_e and lower (higher) $\overline{l_i}$ implies a shift away from (towards) open access and hence, a lower (higher) likelihood of resource degradation.

Total labour allocated to resource extraction is the sum of labour allocated by members and non-members: $L = L_i + L_e$. Overall, the return from extraction for member i is: $l_i e \frac{Y(L)}{L}$, with $Y(L)$ denoting the extraction production function, $\frac{Y(L)}{L}$ is average productivity, and $l_i \leq \overline{l_i}$. The return from the outside option for member i is: $\theta_i A(l_i)$, with θ_i a productivity parameter and $A(l_i)$ the production function of the member's outside option, with $A'(l_i) < 0$ and $A''(l_i) > 0$.

Community member i allocates her labour to maximize her net income:

$$\begin{aligned} \max_{l_i} \pi_i(l_i) &= l_i \frac{Y(L)}{L} + \theta_i A(l_i) \\ s.t. \quad & l_i \leq \overline{l_i} \end{aligned} \tag{4}$$

Assuming that members do not take into account the impact of their labour allocation on the return to extraction, the first-order conditions on the Lagrangian implicitly give the equilibrium labor allocation l_i^*:[37]

$$\begin{aligned}
&\frac{Y(L^*)}{L^*} = \theta_i A'(l_i^*) + \lambda \\
&l_i^* \leq \overline{l_i} \\
&L^* = \int_0^1 l_i^* d_i + L_e
\end{aligned} \tag{5}$$

Three groups of community members can be distinguished in equilibrium (Table A.1). First, *unskilled members*, with low productivity θ_i, are constrained by (effective) management of the commons and would prefer to allocate more labour (possibly all, as in Delacote, 2009) to extraction:

$$\begin{aligned}
&i \in [0, U] \\
&\frac{Y(L^*)}{L^*} > \theta_i A'(\overline{l_i}) \\
&l_i^* = \overline{l_i}
\end{aligned} \tag{6}$$

Second, *middle-skilled members*, with medium productivity θ_i, share their labour allocation between the outside option and extraction:

$$\begin{aligned}
&i \in [U, S] \\
&\theta_i A'(0) \leq \frac{Y(L^*)}{L^*} \leq \theta_i A'(\overline{l_i}) \\
&l_i^* = l_i(\theta_i) \in [0, \overline{l_i}]
\end{aligned} \tag{7}$$

Finally, *skilled members*, with high productivity θ_i, allocate all their labour to their outside option:

$$\begin{aligned}
&i \in [S, 1] \\
&\frac{Y(L^*)}{L^*} \leq \theta_i A'(0) \\
&l_i^* = 0
\end{aligned} \tag{8}$$

[37]As shown in Delacote, 2009, L^* is a fixed point.

	Unskilled	Mid-skilled	Skilled
Members	[0, U]	[U, S]	[S, 1]
θ_i	$< \frac{Y(L^*)/L^*}{A'(\overline{l_i})}$	$\in [\frac{Y(L^*)/L^*}{A'(\overline{l_i})}, \frac{Y(L^*)/L^*}{A'(0)}]$	$\geq \frac{Y(L^*)/L^*}{A'(0)}$
Labour allocation	$\overline{l_i}$	$l_i(\theta_i)$	0

Total labour allocated to extraction is comprised of both unskilled and mid-skilled labour in the community, and labour allocated by non-members.

$$\begin{aligned} L^* &= L_U^* + L_M^* + L_e \\ L_U^* &= \int_0^1 \overline{l_i} d_i = U\overline{l_i} \\ L_M^* &= \int_0^1 l_i^* d_i \end{aligned} \tag{9}$$

A.2 Securing the commons

Securing the commons is characterised as an intervention that gives incentives for external actors to invest in: strengthening the community's capacity to exclude non-members from accessing and benefiting from resource extraction (via more secure, that is, legal exclusion rights) and/or the community's capacity to manage the commons with respect to the extraction behaviour of members (management rights), and/or; improving average productivity in the commons (access and withdrawal rights).

A.2.1 Strengthening community institutions

Strengthening the community's capacity to exclude non-members implies that non-members allocate less of their labour to extraction in the commons, directly influencing the average return to resource extraction, $\frac{Y(L)}{L}$. This direct effect is followed by indirect feedback in terms of labour allocated to extraction by members. Therefore, strengthening the community's capacity to exclude (reducing L_e):

1. directly increases average return from extraction;
   Proof: $\frac{\partial \frac{Y(L^*))}{L^*}}{\partial L_e} > 0$;
2. indirectly increases the number of unskilled members U;
   Proof: the increase in average return implies that more members have private productivity that satisfies equation (6).

3. indirectly increases the level of labour allocated to extraction by mid-skilled members l_i^*;

   Proof: the increase in average return to extraction implies that the condition described in equation (5) is satisfied if l_i^* increases.

4. decreases the number of skilled members $1 - S$

   Proof: the increase in average return implies that fewer memberss have private productivity that satisfies equation (8).

Overall, the total amount of labour allocated to the extraction by members increases if the community's capacity to exclude non-members is stronger (and the labour allocated by non-members decreases). If members do not internalize the negative impact of their labour allocation on the return from extraction, it is possible that total labour allocated to extraction increases, depending on the distribution of θ_i in the population, and on the shape of the resource production function, $Y(L)$. Furthermore, the extent of the effect strongly depends on the relative strength of *de facto* exclusion rights and thus the community's capacity to exclude in the baseline (prior to the intervention), its effectiveness in improving exclusion rights and the distribution of private productivity.

The well-being of skilled members is not impacted while that of unskilled and mid-skilled farmers is not clearly determined.

Strengthening the community's capacity to manage the commons internally (reducing $\overline{l_i}$) has the following effects:

1. decreases the amount of labour allocated by unskilled members $\overline{l_i}$;

   Proof: reducing $\overline{l_i}$ increases the strength of the constraint expressed in equation (5).

2. decreases the number of unskilled members U;

   Proof: reducing $\overline{l_i}$ implies that fewer members have private productivity that satisfies equation (6).

3. decreases the number of skilled members $1 - S$

   Proof: the two previous results imply that the average return from resource extraction increases when $\overline{l_i}$, implying that fewer members have private productivity satisfying condition (8).

Overall, the total amount of labour allocated by members to resource extraction decreases when management rights are made more secure and the community's management capacity improves.[38]

[38] Also note that the allocation of labour to extraction by non-members is likely to increase if management capacity improves while the capacity to exclude remains weak.

The extent of this decline depends on the strength of *de facto* management rights, that is, the baseline strength of the community's management capacity and the effectiveness of the intervention to improve it.

Improving the community's capacity to manage the commons leads to a decrease in the well-being of unskilled members.[39]

A.2.2 Boosting resource production

More secure access and withdrawal rights might drive external investments in higher resource productivity, for example, in the form of facilitating better access to markets. In our set-up, this is characterised as a boost to resource productivity by a factor $\gamma > 1$. The objective function of member i becomes:

$$\begin{aligned} \max_{l_i} \pi_i(l_i) &= \gamma l_i \frac{Y(L)}{L} + \theta_i A(l_i) \\ s.t. \quad & l_i \leq \overline{l_i} \end{aligned} \tag{10}$$

The new allocation of labour according to the three groups of members is now:

	Unskilled	Mid-skilled	Skilled
Members	$[0, \tilde{U}]$	$[\tilde{U}, \tilde{S}]$	$[\tilde{S}, 1]$
θ_i	$< \gamma \frac{Y(\tilde{L_e})/\tilde{L_e}}{A'(\overline{l_i})}$	$\in [\gamma e \frac{\tilde{Y(L)}/\tilde{L}}{A'(\overline{l_i})}, \gamma e \frac{Y(\tilde{L})/\tilde{L}}{A'(0)}]$	$\geq \gamma \frac{\tilde{Y(L)}/\tilde{L}}{A'(0)}$
Labour allocation	$\overline{l_i}$	$l_i(\tilde{\theta_i})$	0

With $l_i(\tilde{\theta_i})$ implicitly defined by:

$$\begin{aligned} \gamma \frac{Y(\tilde{L})}{\tilde{L}} &= \theta_i A'(\tilde{l_i}) + \lambda \\ l_i^* &\leq \overline{l_i} \end{aligned} \tag{11}$$

[39] As our analysis is run in the short term, we do not take into account the possibility that improving a community's management capacity could help secure the commons in the long run, hence the well-being of unskilled members. We note that strengthening the community's capacity to exclude might decrease inequalities between unskilled and skilled members while strengthening management capacity could increase them.

Leading to the new labour allocation:

$$\begin{aligned} \tilde{L} &= \tilde{L_U} + \tilde{L_M} + L_e \\ \tilde{L_U} &= \int_0^1 \overline{l}_i d_i = \overline{l}_i \tilde{U} \\ \tilde{L_M} &= \int_0^1 \tilde{l}_i^* d_i \end{aligned} \tag{12}$$

If we consider that members have a myopic behavior over their pair's labour allocation (i.e, making their decision upon the assumption that $L_e = \tilde{L_e}$) in their objective function, the intervention implies that labour allocated to resource extraction increases with more secure access and withdrawal rights:

$$\begin{aligned} \tilde{U} &> U \\ \tilde{S} &> S \\ \tilde{l}_i &> l_i^* \\ \tilde{L} &> L^* \end{aligned} \tag{13}$$

Implying:

$$Y(\tilde{L})/\tilde{L} < Y(L^*)/L^* \tag{14}$$

If the difference between L^* and $\tilde{L}$ is small (large) enough compared to the factor γ, members may be better off (worse off) with more secure access and withdrawal rights.

Overall, boosting resource production is expected to lead to:

1. an increase in the number of unskilled members

   Proof: the increase in average return implies that more members have private productivity that satisfies equation (6).

2. an increase in labour allocation to resource extraction by mid-skilled farmers

   Proof: the increase in average return to resource extraction implies that the condition described in equation (5) is satisfied if l_i^* increases.

3. a decrease in the number of skilled members $1 - S$

   Proof: the increase in average return implies that fewer members have private productivity that satisfies equation (8).

A.2.3 Impact on well-being

The overall impact of securing the commons on well-being is not straightforward. First, the skilled category is the least impacted: since they do not extract resources, their well-being is not expected to change. Second, the impact on mid-skilled members strongly depends on the distribution of the private productivity parameter. Indeed, when labor allocated by mid-skilled members increases (decreases), the income from their outside option decreases (increases). In other words, one income is replaced by the other. Depending on the shape of the private return function, these members may be better of worse off overall. Unskilled members are the ones most expected to be impacted as resource extraction is their main activity.

B Treated and control Forest Reserves

Table B.1: Impact Areas: Key Attributes

Protected areas	Status	IUCN Management Category	Status Year	Governance type	Management Plan	Management Authority	Area	Management Effectiveness Evaluation
Dzonze	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	66.22 km^2	
Karonga South Escarpment	Designated	VI	2002	Federal or national ministry or agency	None	Department of Forestry	112.12 km^2	
Liwonde	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	284.60 km^2	
Matandwe	Designated	VI	1931	Federal or national ministry or agency	None	Department of Forestry	289.15 km^2	METT 2017, 2022
Mtangatanga	Designated	VI	1935	Federal or national ministry or agency	None	Department of Forestry	91.17 km^2	
Mua-Livulezi	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	133.66 km^2	
Mughese	Designated	VI	1948	Federal or national ministry or agency	None	Department of Forestry	7.69 km^2	
Mvai	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	42.93 km^2	
Ntchisi	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	94.76 km^2	Birdlife IBA 2013
Perekezi	Designated	VI	1935	Federal or national ministry or agency	None	Department of Forestry	157.41 km^2	
Uzumara*	Designated	VI	1948	Federal or national ministry or agency	None	Department of Forestry	7.54 km^2	
Vinthukutu	Designated	VI	1948	Federal or national ministry or agency	None	Department of Forestry	22.13 km^2	
Wilindi	Designated	VI	1948	Federal or national ministry or agency	None	Department of Forestry	8.62 km^2	
Zomba-Malosa*	Designated	VI	1924	Federal or national ministry or agency	None	Department of Forestry	184.3 km^2	

Source: IUCN and UNEP-WCMC (2020).

**Notes*: In the IFMSLP project documents, Uzumara and Phwezi Valley are presented as a single impact area. However, the information from the WDPA included in the table above refers exclusively to Uzumara. Additionally, the Chawa impact area, identified in the project documents as a Proposed Forest Reserve, is not listed in the WDPA and is excluded from the present analysis due to uncertainty regarding its precise location. Similarly, the Masenjere Escarpment, also designated as one of the project's impact areas, does not appear in the WDPA. As with the Chawa Proposed Forest Reserve, it is not included in this study because of uncertainties surrounding its location.Moreover, the WDPA treats Zomba–Malosa as a single protected area, whereas in the dataset used for this analysis, Malosa and Zomba Mountain are recorded as two distinct entities. The areas reported in the table therefore correspond to those in our dataset and may differ slightly from the figures listed in the WDPA. Accordingly, the total area of Zomba–Malosa is computed as the sum of the areas of Zomba Mountain (74.12 km^2) and Malosa (110.18 km^2).

Category VI – Protected areas with sustainable use of natural resources: sites that conserve ecosystems along with their related cultural values and traditional resource-use systems. They are usually large areas that remain mostly in a natural state, with part of the territory managed for sustainable use of natural resources. Low-intensity, non-industrial use of these resources; provided it is compatible with conservation; is explicitly one of the primary objectives (Dudley, 2008).

Birdlife IBA: Birdlife Important Bird and Biodiversity Area Monitoring; METT: Management Effectiveness Tracking Tool.

Table B.2: Control Forest Reserves: Key Attributes

Protected areas	Status	IUCN Management Category	Status Year	Governance type	Management Plan	Management Authority	Area	Management Effectiveness Evaluation
Amalika	Designated	VI	1974	Federal or national ministry or agency	No management plan	Department of Forestry	4.06 km²	
Bangwe	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	42.48 km²	
Bunda	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	6.99 km²	
Bunganya	Designated	VI	1973	Federal or national ministry or agency	No management plan	Department of Forestry	33.95 km²	
Chigumula	Designated	VI	1925	Federal or national ministry or agency	No management plan	Department of Forestry	5.91 km²	
Chikhang'ombe	Designated	VI	2002	Federal or national ministry or agency	No management plan	Department of Forestry	5.92 km²	
Chimaliro	Designated	VI	1926	Federal or national ministry or agency	No management plan	Department of Forestry	160.79 km²	
Chiradzulu	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	15.54 km²	
Chirobwe	Designated	VI	1971	Federal or national ministry or agency	No management plan	Department of Forestry	10.69 km²	
Chisasira	Designated	VI	1935	Federal or national ministry or agency	No management plan	Department of Forestry	24.73 km²	
Cholomwani*							9.27 km²	
Chongoni	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	127.56 km²	
Dedza Mountain	Designated	VI	1926	Federal or national ministry or agency	No management plan	Department of Forestry	32.40 km²	
Dedza-Salima Escarpment	Designated	VI	1974	Federal or national ministry or agency	No management plan	Department of Forestry	382.62 km²	
Dowa Hills	Designated	VI	1974	Federal or national ministry or agency	No management plan	Department of Forestry	23.53 km²	
Dzalanyama	Designated	VI	1922	Federal or national ministry or agency	No management plan	Department of Forestry	989.09 km²	Birdlife IBA 2013
Dzenza	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	11.60 km²	
Kalulu Hills	Designated	VI	1958	Federal or national ministry or agency	No management plan	Department of Forestry	25.86 km²	
Kalwe	Designated	VI	1956	Federal or national ministry or agency	No management plan	Department of Forestry	1.75 km²	
Kaning'ina	Designated	VI	1935	Federal or national ministry or agency	No management plan	Department of Forestry	152.08 km²	
Kanjedza	Designated	VI	1922	Federal or national ministry or agency	No management plan	Department of Forestry	2.21 km²	
Karonga North Escarpment	Designated	VI	2002	Federal or national ministry or agency	No management plan	Department of Forestry	79.08 km²	

Source: IUCN and UNEP-WCMC (2020).
The Cholomwani site is included in our dataset as a forest reserve, but it is not reported in the WDPA. This forest reserve directly borders Kalulu Hills. The areas reported in the table correspond to those in our dataset and may differ slightly from the figures listed in the WDPA.
Birdlife IBA: Birdlife Important Bird and Biodiversity Area Monitoring; METT: Management Effectiveness Tracking Tool.

Table B.3: Control Forest Reserves: Key Attributes (cont.)

Protected areas	Status	IUCN Management Category	Status Year	Governance type	Management Plan	Management Authority	Area	Management Effectiveness Evaluation
Kongwe	Designated	VI	1926	Federal or national ministry or agency	No management plan	Department of Forestry	26.51 km²	
Kuwilwe	Designated	VI	1935	Federal or national ministry or agency	No management plan	Department of Forestry	6.61 km²	
Lichenya	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	3.44 km²	
Lunyangwa	Designated	VI	1935	Federal or national ministry or agency	No management plan	Department of Forestry	4.05 km²	
Mafinga Hills	Designated	VI	1976	Federal or national ministry or agency	No management plan	Department of Forestry	51.84 km²	
Malabvi	Designated	VI	1927	Federal or national ministry or agency	No management plan	Department of Forestry	2.37 km²	
Mangochi	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	402.39 km²	METT 2012
Mangochi Palm	Designated	VI	1980	Federal or national ministry or agency	No management plan	Department of Forestry	5.01 km²	
Masambanjati	Designated	VI	1974	Federal or national ministry or agency	No management plan	Department of Forestry	1.08 km²	
Masenjere	Designated	VI	1930	Federal or national ministry or agency	No management plan	Department of Forestry	2.91 km²	
Matipa	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	10.51 km²	
Mchinji	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	199.71 km²	
Michiru 1)	Designated	VI	1970	Federal or national ministry or agency	No management plan	Department of Forestry	39.67 km²	
Michiru 2)	Designated	VI	2000	Federal or national ministry or agency	No management plan	Department of Forestry	24.11 km²	
Milare	Designated	VI	1949	Federal or national ministry or agency	No management plan	Department of Forestry	0.61 km²	
Mlindi Hill	Designated	VI	2000	Federal or national ministry or agency	No management plan	Department of Forestry	47.91 km²	
Msitolengwe	Designated	VI	1974	Federal or national ministry or agency	No management plan	Department of Forestry	0.98 km²	
Mua-Tsanya	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	10.41 km²	
Mudi	Designated	VI	1922	Federal or national ministry or agency	No management plan	Department of Forestry	0.42 km²	
Mulanje Mountain	Designated	VI	1927	Federal or national ministry or agency	No management plan	Department of Forestry	569.45 km²	
Musisi	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	68.27 km²	
Nalikule	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	0.51 km²	
Namizimu	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	835.54 km²	
Ndirande	Designated	VI	1922	Federal or national ministry or agency	No management plan	Department of Forestry	15.29 km²	
Ngara	Designated	VI	1958	Federal or national ministry or agency	No management plan	Department of Forestry	21.92 km²	
Nkhwadzi	Designated	VI	1927	Federal or national ministry or agency	No management plan	Department of Forestry	17.05 km²	
Nkopola	Designated	VI	1967	Federal or national ministry or agency	No management plan	Department of Forestry	0.57 km²	
North Masatwe	Designated	VI	2000	Federal or national ministry or agency	No management plan	Department of Forestry	4.71 km²	
North Senga	Designated	VI	1958	Federal or national ministry or agency	No management plan	Department of Forestry	11.84 km²	
Phirilongwe	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	483.28 km²	
Ruvuo	Designated	VI	1935	Federal or national ministry or agency	No management plan	Department of Forestry	47.93 km²	
Sambani	Designated	VI	1948	Federal or national ministry or agency	No management plan	Department of Forestry	1.54 km²	
Soche	Designated	VI	1922	Federal or national ministry or agency	No management plan	Department of Forestry	3.91 km²	Birdlife IBA 2013
South Masatwe	Designated	VI	2000	Federal or national ministry or agency	No management plan	Department of Forestry	67.58 km²	
South Senga	Designated	VI	1958	Federal or national ministry or agency	No management plan	Department of Forestry	4.94 km²	
South Viphya	Designated	VI	1958	Federal or national ministry or agency	No management plan	Department of Forestry	1577.28 km²	
Thambani	Designated	VI	1927	Federal or national ministry or agency	Yes	Department of Forestry	50.32 km²	
Thuchila	Designated	VI	1925	Federal or national ministry or agency	No management plan	Department of Forestry	18.54 km²	
Thuma	Designated	VI	1926	Federal or national ministry or agency	No management plan	Department of Forestry	188.74 km²	
Thyolo Mountain	Designated	VI	1924	Federal or national ministry or agency	No management plan	Department of Forestry	8.35 km²	
Tsamba	Designated	VI	1927	Federal or national ministry or agency	No management plan	Department of Forestry	34.79 km²	METT 2012

Source: IUCN and UNEP-WCMC (2020).
The areas reported in the table correspond to those in our dataset and may differ slightly from the figures listed in the WDPA.

Table B.4: Proposed Forest Reserves: Key Attributes

Protected areas	Status	IUCN Management Category	Status Year	Governance type	Management Authority	Management Plan	Area	Management Effectiveness Evaluation
Chanthasha	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	4.98 km²	
Chilenje*							6.33 km²	
Chingale Hills/Namatunu	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	68.34 km²	
Chipala	Proposed	VI	1983	Federal or national ministry or agency	Department of Forestry	No management plan	12.27 km²	
Chombe	Proposed	VI	1992	Federal or national ministry or agency	Department of Forestry	No management plan	55.99 km²	
Choma	Proposed	VI	1972	Federal or national ministry or agency	Department of Forestry	No management plan	71.31 km²	
Dwambazi*							765.84 km²	
Ighembe	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	4.55 km²	
Kalembo Hill	Proposed	VI	1983	Federal or national ministry or agency	Department of Forestry	No management plan	14.46 km²	
Kaombe	Proposed	VI	1964	Federal or national ministry or agency	Department of Forestry	No management plan	14.54 km²	
Kampyongo	Proposed	VI	1992	Federal or national ministry or agency	Department of Forestry	No management plan	6.35 km²	
Kapembe Hill	Proposed	VI	1983	Federal or national ministry or agency	Department of Forestry	No management plan	8.1 km²	
Kawiya	Proposed	VI	1958	Federal or national ministry or agency	Department of Forestry	No management plan	6.44 km²	
Jembya	Proposed	VI	2002	Federal or national ministry or agency	Department of Forestry	No management plan	137.64 km²	
Mahowe	Proposed	VI	2002	Federal or national ministry or agency	Department of Forestry	No management plan	59.17 km²	
Mbula	Proposed	VI	1983	Federal or national ministry or agency	Department of Forestry	No management plan	11.15 km²	
Mkanya Hill	Proposed	VI	2000	Federal or national ministry or agency	Department of Forestry	No management plan	2.75 km²	
Muwanga	Proposed	VI	1983	Federal or national ministry or agency	Department of Forestry	No management plan	7.49 km²	
Mzumangazi	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	78.9 km²	
Nabatata	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	3.45 km²	
Neno Eastern Escarpment	Proposed	VI	2000	Federal or national ministry or agency	Department of Forestry	No management plan	72.06 km²	METT 2012
Nkhoma Hill*							6.04 km²	
Nkula	Proposed	VI	2000	Federal or national ministry or agency	Department of Forestry	No management plan	53.35 km²	
Sonjo	Proposed	VI	*Not Reported*	Federal or national ministry or agency	Department of Forestry	No management plan	9.97 km²	
Therere	Proposed	VI	1992	Federal or national ministry or agency	Department of Forestry	No management plan	20.97 km²	
Wamkurumadzi	Proposed	VI	2000	Federal or national ministry or agency	Department of Forestry	No management plan	16.74 km²	

Source: IUCN and UNEP-WCMC (2020).
The sites of Dwambazi, Nkhoma Hill and Chilenje are included in our dataset as Proposed Forest Reserves, but these are not reported in the WDPA. The areas reported in the table correspond to those in our dataset and may differ slightly from the figures listed in the WDPA.
Category VI – Protected areas with sustainable use of natural resources: sites that conserve ecosystems along with their related cultural values and traditional resource-use systems. They are usually large areas that remain mostly in a natural state, with part of the territory managed for sustainable use of natural resources. Low-intensity, non-industrial use of these resources; provided it is compatible with conservation; is explicitly one of the primary objectives (Dudley, 2008).
METT: Management Effectiveness Tracking Tool.

Table B.5: National Parks and Wildlife Reserves: Key Attributes

Protected areas	Status	IUCN Management Category	Status Year	Governance type	Management Plan	Management Authority	Area	Management Effectiveness Evaluation
Kasungu National Park	Designated	II	1970	Federal or national ministry or agency	Available	Group (Department of National Parks and Wildlife)	2348.11 km²	RAPPAM 2006
Lake Malawi National Park 1)*	Designated	II	1980	Federal or national ministry or agency	Available, being updated	Group (Department of National Parks and Wildlife)	63.01 km²	RAPPAM 2006
Lake Malawi National Park 2) *	Designated	II	1980	Federal or national ministry or agency	Available, being updated	Group (Department of National Parks and Wildlife)	4.93 km²	RAPPAM 2006
Lengwe National Park	Designated	II	1970	Government-delegated management	Available	Group (Department of National Parks and Wildlife in partnership with African Parks)	122.25 km²	RAPPAM 2006; METT 2012, 2017, 2021
Liwonde National Park	Designated	II	1973	Government-delegated management	Available	Group (Department of National Parks and Wildlife in partnership with African Parks)	454.29 km²	METT 2012; RAPPAM 2006
Majete Wildlife Reserve	Designated	IV	1975	Government-delegated management	Available	Group (Department of National Parks and Wildlife in partnership with African Parks)	784.78 km²	RAPPAM 2006; METT 2022
Mwabvi Wildlife Reserve	Designated	IV	1975	Federal or national ministry or agency	Available	Group (Department of National Parks and Wildlife)	147.37 km²	RAPPAM 2006; METT 2017, 2021
Nkhotakota Wildlife Reserve	Designated	IV	1954	Government-delegated management	Available	Group (Department of National Parks and Wildlife in partnership with African Parks)	1800.94 km²	METT 2010; RAPPAM 2006
Nyika National Park	Designated	II	1965	Federal or national ministry or agency	Available	Group (Department of National Parks and Wildlife)	3133.35 km²	RAPPAM 2006 & METT 2022
Vwaza Marsh Wildlife Reserve	Designated	IV	1977	Federal or national ministry or agency	Available	Group (Department of National Parks and Wildlife)	944.27 km²	RAPPAM 2006 & METT 2010, 2022

Source: IUCN and UNEP-WCMC (2020).
The WDPA includes two entries for Lake Malawi National Park, a structure that is also reflected in the dataset used in our analysis. However, the spatial delineation of these entries differs across the two sources. In particular, the WDPA polygons cover a larger area, extending beyond the boundaries of the Lake Malawi National Park polygons available in our dataset. The areas reported in the table correspond to those in our dataset and may differ slightly from the figures listed in the WDPA.
Category II – national parks are extensive natural or near-natural areas that safeguard large-scale ecological processes and the typical species and ecosystems they support. They also provide opportunities for visitors to enjoy spiritual, scientific, educational and recreational activities, as long as these remain compatible with environmental and cultural values (Dudley, 2008).
Category IV – habitat/species management areas are sites set aside to conserve specific species or habitat types, with management actions tailored to that primary goal. In many cases, they involve frequent, active interventions to support those species or habitats, although such intensive management is not strictly required for a site to be classified in this category (Dudley, 2008).
RAPPAM: Rapid Assessment and Prioritisation of Protected Area Management; METT: Management Effectiveness Tracking Tool.

C Nutritional value weights of the FCS

Table C.1: Nutritional value weights per food group

Food Groups	Weights
1) Main staples	
Cereals, Grains and Cereal Products	2
Roots, Tubers, and Plantains	
2) Nuts and Pulses	3
3) Vegetables	1
4) Fruits	1
5) Meat, Fish and Animal Products	4
6) Milk/Milk Products	4
7) Sugars/Sugar Products/Honey	0.5
8) Fats/Oils	0.5

The food groups included in the World Food Programme's Food Consumption Score (FCS) comprise: main staples; pulses and nuts; vegetables; fruits; meat, fish, and other animal-source foods; milk and milk products; sugars, sugar products, and honey; and fats and oils. For each food group, consumption frequency ranges from 0 to 7, corresponding to the number of days during the previous week in which the group was consumed. Higher weights are assigned to food groups that are rich in protein, micronutrients, and energy, such that staple foods receive lower weights than more nutrient-dense animal-source products (INDDEX Project, 2018).

Moreover, the FCS is strongly correlated with the Household Dietary Diversity Score (HDDS), which is defined as the number of distinct food groups consumed by a household over a given reference period and is typically computed using 12 food groups. Unlike the FCS, the HDDS does not account for consumption frequency or differences in the nutritional value of food groups. As highlighted by Maxwell et al. (2013), and confirmed in our data, both indicators are closely related. In most contexts, the FCS and the HDDS can therefore be used as measures of household dietary diversity and as valid proxies for households' access to energy-sufficient diets (Maxwell et al., 2013).

D Descriptive statistics

Table D.1: Descriptive statistics for the main variables of this analysis

Main variables (measured at baseline)	**2016**							**2019**						
	Treated group (152 HHs at baseline)			Control group (922 HHs at baseline)			***t-test diff in means***	Treated group (186 HHs at baseline)			Control group (1,114 HHs at baseline)			***t-test diff in means***
	Obs.	**Mean**	**SD**	**Obs.**	**Mean**	**SD**		**Obs.**	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	
Food Composition Score	152	48.717	18.294	922	50.101	20.061	1.384	186	48.774	17.542	1114	50.119	20.497	1.345
Asset value (log. real terms. MWK)	127	8.319	1.7	802	9.035	1.964	0.716***	155	8.300	1.697	966	9.0125	1.959	0.712***
Non-food expenditures. week (log. real value. MWK)	126	4.171	1.641	874	4.842	1.686	0.671***	155	4.070	1.562	1052	4.897	1.665	0.827***
Forest loss (%) - 11km buffer	152	0.058	0.054	922	0.046	0.080	-0.012*	186	0.057	0.053	1114	0.0437	0.078	-0.013**
Household size	152	5.395	2.493	922	5.198	2.297	-0.196	186	5.521	2.445	1114	5.284	2.259	-0.238
Livestock ownership (1=yes)	152	0.546	0.499	922	0.436	0.496	-0.110**	186	0.564	0.497	1114	0.425	0.495	-0.139***
Distance to pop. center (km)	152	33.621	18.156	922	25.688	17.154	-7.933***	186	34.111	18.024	1114	25.829	17.135	-8.282***
Distance to lakes (km)	152	56.566	46.974	922	61.140	26.928	4.573*	186	52.633	43.826	1114	61.986	26.414	9.353***
Forest cover (%) - 10 km buffer	152	17.863	4.915	922	13.061	7.726	-4.803***	186	17.907	4.902	1114	12.802	7.492	-5.105***
Elevation (m)	152	819.987	399.811	922	978.64	239.957	158.653	186	826.704	382.408	1114	977.689	236.339	150.985***

Note: Descriptive statistics for the main variables of the analysis measured at baseline (year 2010), used eiher as outcomes, matching variables or both.

E Trends

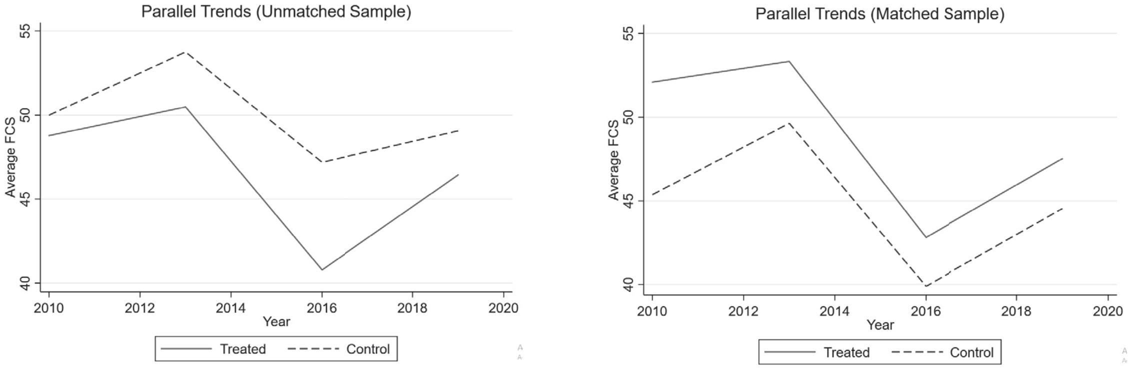

Figure E.1: Trends for the FCS (unmatched and matched sample)

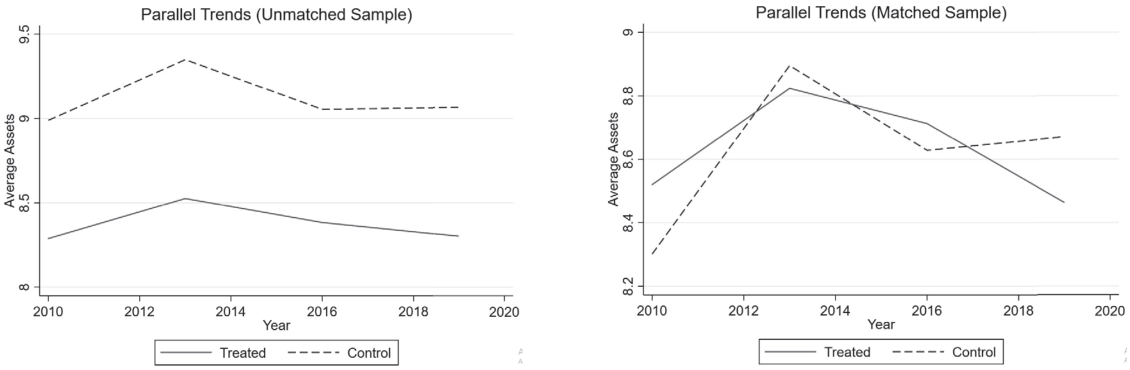

Figure E.2: Trends for Assets (unmatched and matched sample)

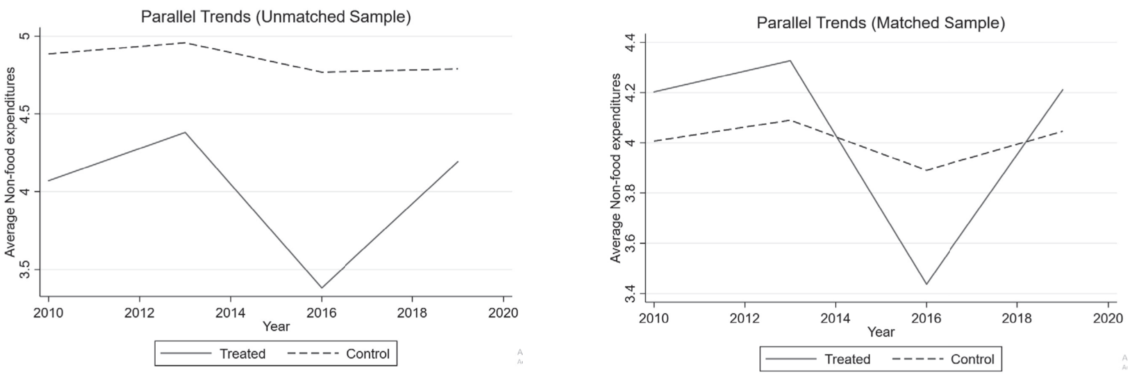

Figure E.3: Trends for Non-food expenditures (unmatched and matched sample)

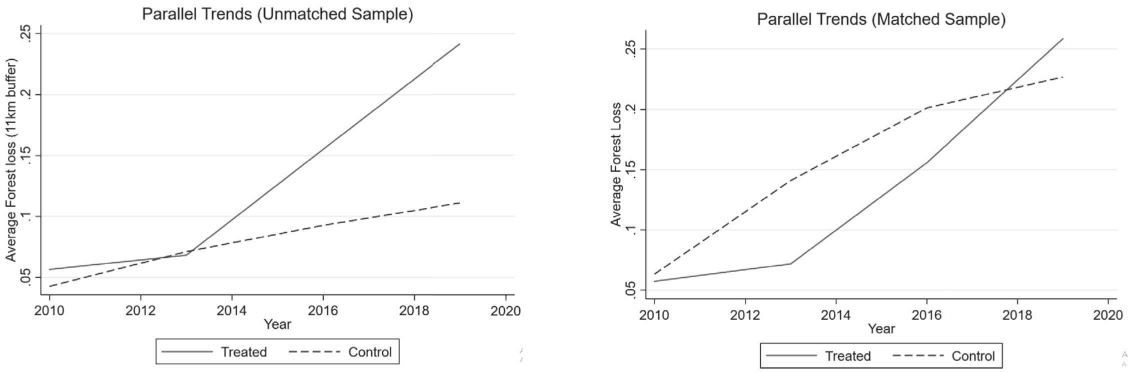

Figure E.4: Trends for Forest loss (unmatched and matched sample)

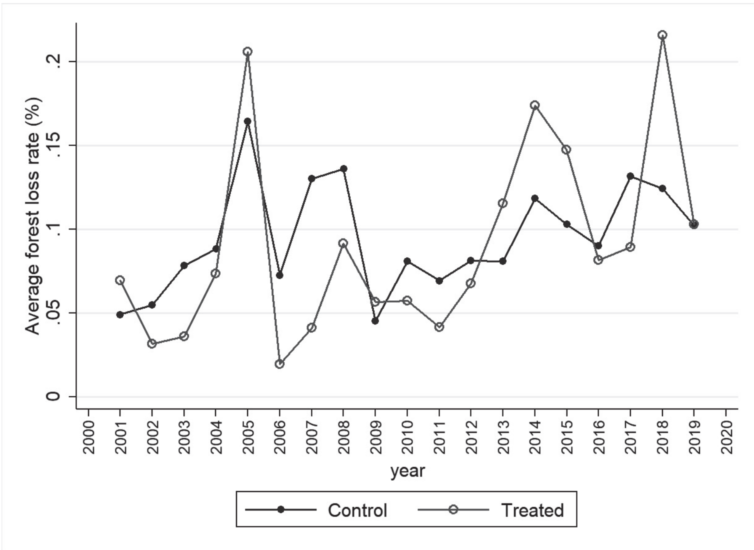

Figure E.5: Trends in forest loss, 2001–2019 (2010–2016 sample)

Notes: Share of forest loss (%) relative to 2000 forest cover between 2001 and 2019, using Hansen et al. (2013) data, by treatment status. The indicator is computed within 11 km buffer zones around enumeration areas (EAs) included in the unmatched 2010–2016 analytical sample.

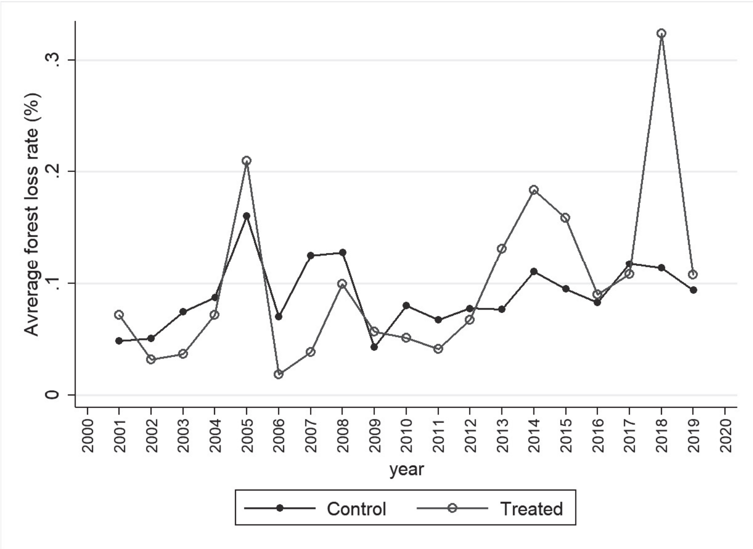

Figure E.6: Trends in forest loss, 2001 to 2019 (2010–2019 sample)

Notes: Share of forest loss (%) relative to 2000 forest cover between 2001 and 2019, using Hansen et al. (2013) data, by treatment status. The indicator is computed within 11 km buffer zones around enumeration areas (EAs) included in the unmatched 2010–2019 analytical sample.

F Covariate balancing tests

Table F.1: Balancing test - 2016 sample

	Unmatched (U)	Mean		Bias	T-test	
Variables	**Matched (M)**	**Treated**	**Control**	**%**	**t**	**p>|t|**
Household size	U	5.791	5.371	17	1.74	0.083
	M	5.791	5.421	15	1.11	0.270
Livestock ownership (1=yes)	U	0.573	0.448	25	2.45	0.015
	M	0.573	0.559	2.8	0.21	0.835
Asset value (log. real terms. MWK)	U	8.575	9.091	-29.3	-2.72	0.007
	M	8.575	8.335	13.6	1.12	0.263
Non-food expenditures. week (log. real value. MWK)	U	4.295	4.998	-42	-4.09	0.000
	M	4.295	3.977	19	1.57	0.119
Distance to major population center (km)	U	33.328	24.211	50.8	5.19	0.000
	M	33.328	35.32	-11.1	-0.82	0.412
Distance to lakes (km)	U	56.52	61.059	-11.8	-1.50	0.133
	M	56.52	47.807	22.6	1.62	0.108
Forest cover (%) - 10 km buffer	U	17.592	13.096	67.5	5.69	0.000
	M	17.592	17.711	-1.8	-0.12	0.908
Elevation (m)	U	818.36	988.79	-50.7	-6.39	0.000
	M	818.36	844.59	7.8	-0.56	0.578

Table F.2: Balancing test - 2019 sample

Variables	**Unmatched (U)** / **Matched (M)**	Mean **Treated**	Mean **Control**	Bias **%**	T-test **t**	T-test **p>|t|**
Household size	U	5.934	5.439	20.4	2.31	0.021
	M	5.934	5.431	20.8	1.69	0.092
Livestock ownership (1=yes)	U	0.6176	0.436	37.0	4.00	0.000
	M	0.6176	0.587	6.3	0.52	0.603
Asset value (log. real terms. MWK)	U	8.529	9.069	–30.5	-3.15	0.002
	M	8.529	8.212	17.9	1.57	0.117
Non-food expenditures. week (log. real value. MWK)	U	4.2	5.047	-52.2	-5.54	0.000
	M	4.2	4.069	8.1	0.72	0.470
Distance to major population center (km)	U	33.594	24.209	52.4	5.94	0.000
	M	33.594	36.229	-14.7	-1.23	0.220
Distance to lakes (km)	U	52.214	61.721	–26.2	–3.62	0.000
	M	52.214	47.405	13.3	1.04	0.300
Forest cover (%) - 10 km buffer	U	17.879	12.82	77.5	7.32	0.000
	M	17.879	17.647	3.6	0.25	0.802
Elevation (m)	U	822.93	985.02	–50.2	–6.88	0.000
	M	822.93	825.84	–0.9	- -0.07	0.943

G Additional forest loss results

Table G.1: Treatment effect on loss within customary forests and forest reserves

	2016		2019	
Dependent variables	**Cust. loss**	**FR loss**	**Cust. loss**	**FR loss**
	(1)	(2)	(3)	(4)
Treatment	-0.00470	-0.0479	-0.0121	-0.0379
	(0.0392)	(0.0360)	(0.0430)	(0.0302)
Post treatment	0.112**	0.172	0.150***	0.270
	(0.0512)	(0.109)	(0.0513)	(0.193)
Treatment X Post	-0.0278	-0.173	0.0470	-0.215
	(0.0629)	(0.109)	(0.120)	(0.199)
Observations	1,150	642	1,490	695
R-squared	0.066	0.107	0.126	0.154

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. Columns 1 & 3 report the treatment effect on forest loss within customary forests located within an 11 km radius of the EA, while columns 2 & 4 show the treatment effect within forest reserves that intersect within the same 11 km radius.

Table G.2: Treatment effect on forest loss (total, customary, forest reserve) - Restricted sample

	2016			2019		
Dependent variables	**Total loss**	**Cust. loss**	**FR loss**	**Total loss**	**Cust. loss**	**FR loss**
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.00697	-0.00633	0.00322	0.0229	0.0247	-0.0276
	(0.0335)	(0.0344)	(0.0487)	(0.0283)	(0.0291)	(0.0251)
Post treatment	0.138**	0.134**	0.383**	0.0783**	0.0804**	0.111**
	(0.0669)	(0.0657)	(0.184)	(0.0317)	(0.0332)	(0.0437)
Treatment X Post	-0.0337	-0.0336	-0.230	0.0515	0.0404	0.232
	(0.0806)	(0.0803)	(0.216)	(0.0829)	(0.0891)	(0.179)
Observations	940	937	331	1,600	1,600	673
R-squared	0.082	0.076	0.075	0.057	0.051	0.105

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. For these estimates, we restricted the sample to households residing within 10 km of their 2010 location, the baseline year. This restriction was added because the reported walking times used to infer distances correspond to conditions in 2010, and households that later moved farther away would invalidate the link between reported travel time and actual forest access. The buffer used to estimate potential forest loss was derived from households' reported walking time in 2010 to reach their firewood collection sites. Assuming that approximately 10 minutes correspond to 1 km of walking distance, the average reported travel time of 60 minutes implies a distance of about 6 km. To this distance, we add a 5 km margin to account for the random spatial displacement of enumeration areas (EAs). This yields an approximate 11 km radius within which forest resources were likely to be accessed.

H Overview of robustness checks

H.1 Robustness checks using the 2010-2016 sample

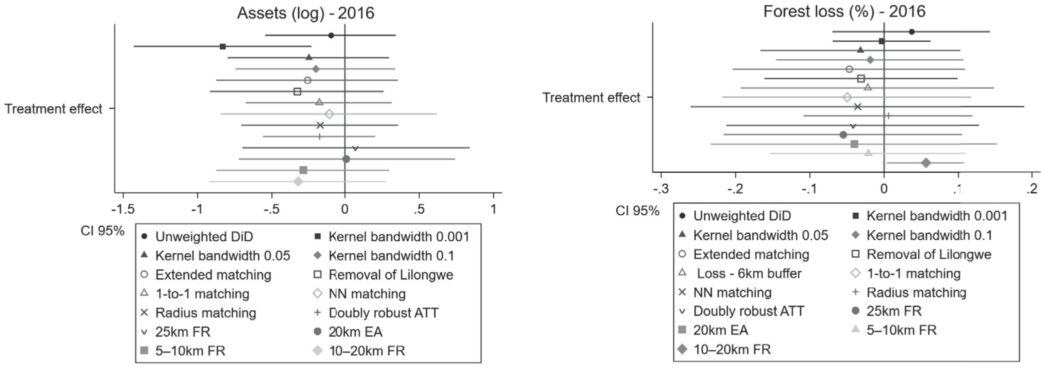

Figure H.1: Overview of robustness checks (2016)

Notes: Using the 2010–2016 sample, the figures present an overview of the robustness checks conducted for the asset value and forest loss share outcomes, which are discussed in detail later in this appendix. Specifically, we assess the sensitivity of our findings to a range of alternative specifications, including an unweighted difference-in-differences estimator; alternative matching strategies and matching specifications; and the exclusion of the capital city and its surrounding areas. In addition, for the forest loss share outcome, we test an alternative outcome definition by using a more restricted buffer around Enumeration Areas (EAs) to measure forest loss (6km instead of 11km). We also examine robustness to the use of a doubly robust estimator; to alternative definitions of treatment and control groups based on distance to Forest Reserve (FR) boundaries (including treated households located 5–25 km, 5–10 km, or 10–20 km from treated FR boundaries and at least 25 km or 10 km from untreated FR boundaries, with symmetric definitions for untreated households); and to spatial separation between EAs, by restricting the sample to cases in which EAs from different groups are located at least 20 km apart.

H.2 Robustness checks using the 2010-2019 sample

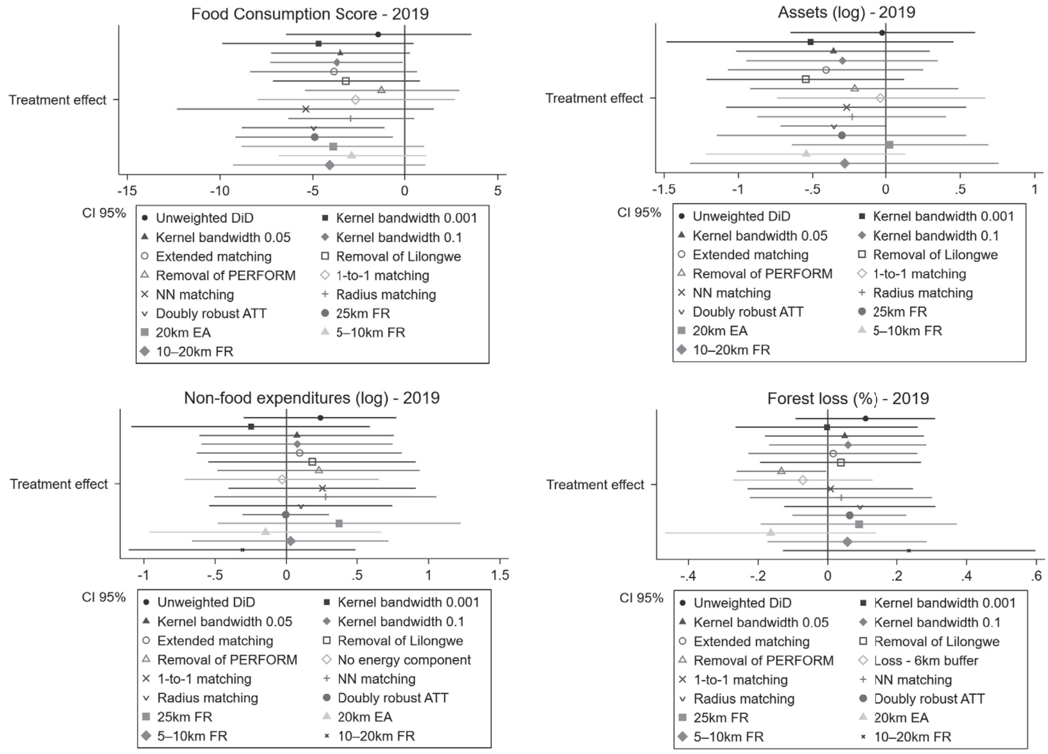

Figure H.2: Overview of robustness checks (2019)

Notes: Using the 2010–2019 sample, the figures present an overview of the robustness checks conducted for our main outcomes, which are discussed in detail later in this appendix. Specifically, we assess the sensitivity of our findings to a range of alternative specifications, including an unweighted difference-in-differences estimator; alternative matching strategies and matching specifications; and the exclusion of the capital city and its surrounding areas, as well as the PERFORM districts. In addition, for the non-food expenditure and forest loss outcomes, we test alternative outcome definitions by excluding energy-related purchases from non-food expenditures and by using a more restricted buffer around Enumeration Areas (EAs) to measure forest loss. We also examine robustness to the use of a doubly robust estimator; to alternative definitions of treatment and control groups based on distance to Forest Reserve (FR) boundaries (including treated households located 5–25 km, 5–10 km, or 10–20 km from treated FR boundaries and at least 25 km or 10 km from untreated FR boundaries, with symmetric definitions for untreated households); and to spatial separation between EAs, by restricting the sample to cases in which EAs from different groups are located at least 20 km apart.

I Robustness checks: full results

I.1 Testing policy effect using 2013 sample

Table I.1: Treatment effect on policy outcomes (2013 sample)

Dependent variables	**FCS** (1)	**Assets** (2)	**Exp.** (3)	**Total loss** (4)
Treatment	6.230**	0.0770	0.0582	-0.0110
	(2.758)	(0.218)	(0.288)	(0.0383)
Post treatment	1.938	0.633***	-0.0529	0.0720*
	(2.488)	(0.106)	(0.204)	(0.0377)
Treatment X Post	-1.348	-0.334	0.323	-0.0538
	(2.872)	(0.231)	(0.278)	(0.0422)
Observations	1,022	973	962	1,022
R-squared	0.030	0.025	0.008	0.064

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: DiD estimation using weights from Kernel matching.

I.2 Doubly-robust estimator

Table I.2: Doubly-robust estimator (2016)

Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**Cust. loss**	**FR loss**
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment X Post	-8.835**	-0.179	-0.750***	-0.042	-0.043	0.076
	3.916	0.195	0.280	0.087	0.098	1.107
Observations	1,736	1,652	1,586	1,736	1,736	788

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Doubly-robust estimator (Sant'Anna & Zhao, 2020).

Table I.3: Doubly-robust estimator (2019)

Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**Cust. loss**	**FR loss**
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment X Post	-4.959***	-0.356*	-0.005	0.063	0.057	0.120
	1.976	0.184	0.155	0.084	0.091	0.208
Observations	2,094	1,932	1,904	2,094	2,056	902

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Doubly-robust estimator (Sant'Anna & Zhao, 2020).

I.3 Impact of alternative matching variable specifications on the main results

Table I.4: Extended matching strategy

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	6.858**	0.0823	0.0550	-0.0197	6.494**	0.256	0.00904	-0.0150
	(2.557)	(0.323)	(0.359)	(0.0453)	(3.121)	(0.302)	(0.308)	(0.0377)
Post treatment	-3.213*	0.253	-0.213	0.137*	-0.430	0.367***	-0.0441	0.182***
	(1.702)	(0.177)	(0.184)	(0.0709)	(1.934)	(0.108)	(0.190)	(0.0630)
Treatment X Post	-8.201**	-0.259	-0.604	-0.0468	-3.864*	-0.410	0.0924	0.0154
	(3.588)	(0.304)	(0.407)	(0.0777)	(2.236)	(0.326)	(0.356)	(0.120)
Observations	1,050	1,016	988	1,050	1,220	1,163	1,152	1,220
R-squared	0.070	0.003	0.039	0.085	0.030	0.007	0.000	0.144

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. *Matching variables*: household size (count); livestock ownership (1=yes); value of durable assets (log, real terms, MWK); non-food expenditures in the past week (log, real terms, MWK); distance of households' EA to the closest major population center (km); elevation (m); average forest cover in an area of 10 km around EA (%); distance of households' EA to the closest major lake (Lake Niassa, Chilwa, or Malombe); presence of a village health clinic in the community (1 = yes); % under agriculture within approx 1 km buffer.

I.4 Treatment areas

Table I.5: Households treated in Phase 1

	2016				2019			
Dependent variables	FCS (1)	Assets (2)	Exp. (3)	Total loss (4)	FCS (5)	Assets (6)	Exp. (7)	Total loss (8)
Treatment	4.167	0.211	0.440	-0.0277	4.697	0.0218	0.281	-0.0366
	(2.807)	(0.277)	(0.379)	(0.0533)	(3.101)	(0.239)	(0.395)	(0.0574)
Post treatment	-7.358***	0.166	-0.208	0.115	-2.477	0.442***	0.0886	0.153**
	(1.946)	(0.130)	(0.239)	(0.0797)	(1.801)	(0.111)	(0.219)	(0.0745)
Treatment X Post	1.524	0.0132	0.0458	0.0776	-0.305	-0.232	-0.0225	0.125
	(3.143)	(0.207)	(0.376)	(0.0941)	(2.575)	(0.213)	(0.278)	(0.110)
Observations	2,848	2,792	2,722	2,848	3,194	3,077	3,026	3,194
R-squared	0.046	0.006	0.018	0.088	0.021	0.010	0.006	0.138

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching.

Table I.6: Treatment effect on households located 25-45 km from FR boundaries

	2016			2019		
Dependent variables	**FCS** (1)	**Assets** (2)	**Exp.** (3)	**FCS** (4)	**Assets** (5)	**Exp.** (6)
Treatment	3.644	0.0460	-0.527	-4.217	1.523	0.244
	(3.903)	(0.335)	(0.815)	(8.678)	(1.323)	(0.694)
Post treatment	0.500	-0.0413	-0.0205	-5.988	0.918	-0.113
	(3.728)	(0.238)	(0.182)	(11.15)	(1.442)	(0.143)
Treatment X Post	-2.625	0.765	0.676	13.37	-0.567	0.199
	(4.116)	(0.480)	(0.848)	(11.73)	(1.482)	(0.279)
Observations	89	88	80	125	121	113
R-squared	0.017	0.101	0.025	0.043	0.191	0.013

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: DiD estimations are conducted using weights derived from kernel matching. Estimations for forest-related outcomes could not be performed due to the limited sample size. In the 2010–2016 sample, the control group consists of 198 observations, while the treated group includes 852 observations. For the 2010–2019 sample, the control group comprises 267 observations and the treated group 1,028 observations. In these estimations, treated households are located between 25 and 45 km from the boundary of a treated FR, whereas untreated households are located between 25 and 45 km from the boundary of an untreated FR. In addition, control households are situated at least 25 km away from any treated FR. The reverse approach was not adopted, as it would have resulted in the loss of a substantial number of treated observations. Finally, it is important to note that a large share of treated households fell outside the common support after matching and were therefore excluded from the final estimations.

Table I.7: Treatment effect - 5 to 10 km from the boundaries of FR

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	5.711**	0.181	0.188	-0.0198	5.866*	0.312	0.157	-0.00573
	(2.494)	(0.308)	(0.370)	(0.0456)	(2.937)	(0.311)	(0.309)	(0.0358)
Post treatment	-5.176***	0.282*	-0.0189	0.111*	-1.445	0.501***	0.0194	0.141***
	(1.615)	(0.152)	(0.267)	(0.0573)	(1.639)	(0.135)	(0.166)	(0.0504)
Treatment X Post	-6.238*	-0.288	-0.798*	-0.0213	-2.850	-0.544	0.0289	0.0563
	(3.546)	(0.290)	(0.451)	(0.0656)	(1.985)	(0.336)	(0.343)	(0.114)
Observations	1,196	1,161	1,128	1,196	1,552	1,472	1,461	1,552
R-squared	0.077	0.004	0.034	0.069	0.029	0.011	0.003	0.138

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. Treated households are situated 5 to 10 km from the boundary of a treated FR, while untreated households are located 5 to 10 km from the boundary of an untreated FR. In addition, treated households are positioned at least 10 km away from any untreated FR, and untreated households are, in turn, located at least 10 km away from any treated FR.

Table I.8: Treatment effect - 5 to 25 km from the boundaries of a FR

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	7.584***	0.129	0.125	-0.0166	8.714***	0.167	0.114	-0.0273
	(2.488)	(0.426)	(0.342)	(0.0447)	(2.985)	(0.377)	(0.335)	(0.0571)
Post treatment	-5.812***	0.120	-0.257	0.153**	0.103	0.338***	-0.393*	0.140***
	(1.538)	(0.155)	(0.167)	(0.0681)	(1.899)	(0.125)	(0.199)	(0.0506)
Treatment X Post	-7.188**	0.0704	-0.638	-0.0549	-4.902**	-0.303	0.372	0.0898
	(3.108)	(0.381)	(0.488)	(0.0800)	(2.117)	(0.418)	(0.423)	(0.140)
Observations	1,100	1,070	1,040	1,100	1,370	1,308	1,299	1,370
R-squared	0.109	0.005	0.043	0.104	0.047	0.006	0.014	0.148

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. Did estimation with weights from Kernel matching. Treated households are situated 5 to 25 km from the boundary of a treated FR, while untreated households are located 5 to 25 km from the boundary of an untreated FR. In addition, treated households are positioned at least 25 km away from any untreated FR, and untreated households are, in turn, located at least 25 km away from any treated FR.

Table I.9: Minimum distance of 20 km between EAs across groups

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	9.595***	0.0573	0.0993	0.00244	7.557**	-0.131	-0.0878	-0.0119
	(2.979)	(0.230)	(0.321)	(0.0443)	(3.636)	(0.308)	(0.269)	(0.0550)
Post treatment	-2.093	0.294*	0.235	0.171**	-0.443	0.389***	0.479*	0.266***
	(2.150)	(0.163)	(0.269)	(0.0803)	(2.119)	(0.135)	(0.253)	(0.0980)
Treatment X Post	-10.37**	0.00925	-0.728**	-0.0400	-3.906	0.0245	-0.147	-0.164
	(4.927)	(0.363)	(0.347)	(0.0959)	(2.459)	(0.330)	(0.404)	(0.150)
Observations	1,546	1,517	1,491	1,519	1,636	1,571	1,572	1,552
R-squared	0.082	0.009	0.020	0.119	0.035	0.016	0.017	0.159

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. Elevation is excluded from the set of matching covariates, as its inclusion leads to a substantial loss of observations due to lack of common support.

Table I.10: Treatment effect on households located 10-20 km from FR boundaries

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.128	-0.420	-0.801	0.0210	-0.824	-0.566	-1.005*	0.0262
	(3.166)	(0.414)	(0.636)	(0.0294)	(2.906)	(0.502)	(0.539)	(0.0317)
Post treatment	-2.682*	0.0524	0.00115	-0.000815	-1.753	0.178*	-0.0629	0.0187
	(1.475)	(0.127)	(0.103)	(0.0206)	(1.589)	(0.0958)	(0.117)	(0.0114)
Treatment X Post	-10.69**	-0.323	-1.084**	0.0565**	-4.097	-0.285	-0.308	0.234
	(4.018)	(0.293)	(0.505)	(0.0258)	(2.541)	(0.508)	(0.389)	(0.177)
Observations	1,212	1,117	1,124	1,212	1,428	1,289	1,315	1,428
R-squared	0.020	0.008	0.049	0.036	0.006	0.012	0.033	0.335

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Unweighted Did estimations are presented in this table. Matching was not implemented because of the limited sample size, particularly for the treated group. In the 2010 - 2016 sample, the control group consists of 1,090 whereas the treated group includes 122 observations. For the 2010 - 2019 sample, the control group includes of 1,282 observations and the treated group 146 observations. Moreover, in these estimations, treated households are situated 10 to 20 km from the boundary of a treated FR, while untreated households are located 10 to 20 km from the boundary of an untreated FR. In addition, treated households are positioned at least 20 km away from any untreated FR, and untreated households are, in turn, located at least 20 km away from any treated FR.

I.5 Treatment Effect without PERFORM Districts (2019)

Table I.11: Treatment Effect without PERFORM Districts (2019)

Dependent variables	**FCS** (1)	**Assets** (2)	**Exp.** (3)	**Total loss** (4)
Treatment	1.669	0.0242	-0.0602	-0.00803
	(2.552)	(0.289)	(0.340)	(0.0471)
Post treatment	-1.854	0.480***	-0.0888	0.146***
	(1.680)	(0.132)	(0.184)	(0.0489)
Treatment X Post	-1.250	-0.217	0.227	-0.133**
	(2.072)	(0.349)	(0.352)	(0.0637)
Observations	1,339	1,273	1,266	1,339
R-squared	0.007	0.016	0.001	0.096

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching.

I.6 Composition of the household sample

Table I.12: Unweighted Difference-in-Differences (2016)

Dependent variables	**FCS** (1)	**Assets** (2)	**Exp.** (3)	**Total loss** (4)
Treatment	-1.384	-0.717*	-0.671*	0.0124
	(4.074)	(0.361)	(0.339)	(0.0236)
Post treatment	-2.215*	0.0327	-0.0573	0.0580
	(1.117)	(0.0956)	(0.103)	(0.0370)
Treatment X Post	-6.802**	-0.102	-0.691**	0.0371
	(3.120)	(0.221)	(0.334)	(0.0531)
Observations	2,148	1,934	1,957	2,148
R-squared	0.016	0.019	0.040	0.031

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation without any weights from PSM.

Table I.13: Unweighted Difference-in-Differences (2019)

Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)
Treatment	-1.345	-0.712**	-0.827***	0.0134
	(3.909)	(0.345)	(0.285)	(0.0225)
Post treatment	-0.754	0.0802	-0.0863	0.0725***
	(1.273)	(0.0832)	(0.0979)	(0.0264)
Treatment X Post	-1.432	-0.0252	0.237	0.108
	(2.493)	(0.311)	(0.267)	(0.100)
Observations	2,600	2,275	2,358	2,600
R-squared	0.002	0.016	0.018	0.078

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation without any weights from PSM.

Table I.14: Treatment effect without Lilongwe & Lilongwe non-city (2016)

Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)
Treatment	7.925***	0.278	0.349	-0.0117
	(2.730)	(0.303)	(0.347)	(0.0396)
Post treatment	-2.746	0.322**	-0.00542	0.121**
	(1.809)	(0.149)	(0.174)	(0.0553)
Treatment X Post	-8.668**	-0.328	-0.812*	-0.0311
	(3.647)	(0.289)	(0.404)	(0.0639)
Observations	990	958	933	990
R-squared	0.075	0.006	0.033	0.076

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching.

Table I.15: Treatment effect without Lilongwe & Lilongwe non-city (2019)

Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)
Treatment	6.134**	0.371	0.163	-0.0188
	(2.989)	(0.312)	(0.339)	(0.0437)
Post treatment	-1.128	0.503***	-0.133	0.160***
	(1.618)	(0.121)	(0.198)	(0.0514)
Treatment X Post	-3.166	-0.546	0.181	0.0374
	(1.969)	(0.331)	(0.360)	(0.115)
Observations	1,196	1,137	1,128	1,196
R-squared	0.030	0.012	0.007	0.143

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching.

I.7 Outcome measures

Table I.16: Non-food expenditures excluding energy-related expenditures

Dependent variable	Exp. (no energy exp.)	
	2016	2019
Treatment	0.436	0.534
	(0.380)	(0.322)
Post treatment	0.606***	0.599***
	(0.187)	(0.182)
Treatment X Post	-0.947**	-0.0302
	(0.353)	(0.339)
Observations	1,152	1,349
R-squared	0.023	0.056

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: DiD estimation with weights from Kernel matching. The main outcome variable is weekly non-food expenditure excluding energy-related items (i.e. charcoal, paraffin, and kerosene). In the set of covariates used for the matching procedure, energy-related purchases are also removed from the non-food expenditure measure. The results in this table suggest that although households might have more access to, e.g. fuelwood, they are not reducing expenditures on energy, a result that is consistent with the possibility that the IFMSLP did not lead to more resource extraction if customary areas and Reserves were already open access in the baseline (see Section 6).

Table I.17: Share of gross forest loss within a 6 km buffer around the EA

Dependent variable	Forest loss (6km)	
	2016	2019
Treatment	-0.0129	-0.0209
	(0.0500)	(0.0560)
Post treatment	0.116*	0.134**
	(0.0670)	(0.0531)
Treatment X Post	-0.0219	-0.0717
	(0.0847)	(0.0995)
Observations	1,150	1,490
R-squared	0.049	0.051

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. The main outcome variable is the share of gross forest loss within a 6 km buffer around EA, intended to capture reductions in the distance households travel to collect firewood.

I.8 Sensitivity due to the influence of weather shocks on DiD estimates

Table I.18: Treatment effect on the SPEI

Dependent variables	**SPEI**$_t$	**Shock**$_t$	**SPEI**$_{t\text{-}1}$	**Shock**$_{t\text{-}1}$
	(1)	(2)	(3)	(4)
Treatment	0.0604	0.0535	-0.00637	0.0982
	(0.248)	(0.137)	(0.153)	(0.183)
Post treatment	-0.898***	0.282**	0.507***	-0.0548
	(0.130)	(0.110)	(0.121)	(0.0995)
Treatment X Post	-0.254	0.280	-0.136	0.242
	(0.239)	(0.246)	(0.462)	(0.367)
Observations	1,018	1,018	1,018	1,018
R-squared	0.519	0.271	0.169	0.091

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching. In columns 1 & 3 the outcome variable is the continuous SPEI for periods $_t$ and $_{t\text{-}1}$ respectively. In columns 2 & 4 the outcome variable is a binary variable equal to 1 when the SPEI is at least 1 in absolute value, capturing potential wet or dry shocks.

I.9 Sensitivity of results to Kernel bandwidth choices

Table I.19: Treatment effect using varying Kernel bandwidths (2016)

	2016											
Kernel bandwidths	**0.001**				**0.05**				**0.1**			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	7.857*	0.459	0.656	-0.00931	7.003***	0.140	0.191	-0.00995	5.474**	-0.00894	-0.0284	-0.00843
	(4.027)	(0.293)	(0.488)	(0.0223)	(2.561)	(0.299)	(0.351)	(0.0390)	(2.531)	(0.303)	(0.349)	(0.0372)
Post treatment	-2.387	0.388	0.431	0.0704***	-3.325**	0.244**	-0.0645	0.122**	-3.528**	0.197*	-0.114	0.108*
	(2.570)	(0.244)	(0.484)	(0.0246)	(1.603)	(0.116)	(0.197)	(0.0591)	(1.495)	(0.109)	(0.176)	(0.0546)
Treatment X Post	-12.02**	-0.832***	-1.573**	-0.00331	-8.089**	-0.250	-0.753*	-0.0318	-7.886**	-0.203	-0.703*	-0.0187
	(5.104)	(0.296)	(0.677)	(0.0326)	(3.534)	(0.272)	(0.412)	(0.0672)	(3.486)	(0.269)	(0.403)	(0.0632)
Observations	528	511	500	528	1,678	1,637	1,604	1,678	1,736	1,694	1,661	1,736
R-squared	0.090	0.018	0.064	0.073	0.070	0.003	0.033	0.074	0.062	0.003	0.040	0.067

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching, using varying bandwidths.

Table I.20: Treatment effect using varying Kernel bandwidths (2019)

	2019											
Kernel bandwidths	**0.001**				**0.05**				**0.1**			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	5.439*	0.424	0.0713	-0.0222	6.140**	0.199	0.0498	-0.00946	5.292*	0.0412	-0.0901	-0.00585
	(3.173)	(0.365)	(0.393)	(0.0410)	(2.912)	(0.300)	(0.308)	(0.0368)	(2.822)	(0.303)	(0.305)	(0.0336)
Post treatment	1.873	0.490	0.156	0.187**	-0.807	0.317***	-0.0250	0.149***	-0.588	0.256**	-0.0278	0.139***
	(1.824)	(0.301)	(0.236)	(0.0701)	(1.503)	(0.110)	(0.161)	(0.0507)	(1.395)	(0.0986)	(0.149)	(0.0480)
Treatment X Post	-4.704*	-0.515	-0.249	-0.00269	-3.488*	-0.360	0.0733	0.0484	-3.706**	-0.299	0.0761	0.0580
	(2.555)	(0.478)	(0.413)	(0.129)	(1.874)	(0.326)	(0.340)	(0.114)	(1.789)	(0.322)	(0.335)	(0.113)
Observations	626	597	592	626	2,088	2,007	1,993	2,088	2,090	2,009	1,995	2,090
R-squared	0.017	0.014	0.002	0.142	0.028	0.005	0.001	0.137	0.020	0.004	0.000	0.137

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from Kernel matching, using varying bandwidths.

I.10 Robustness of treatment effects under alternative matching strategies

Table I.21: One-to-one matching

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	5.081	-0.194	0.153	0.0105	5.310	-0.0237	-0.275	0.00391
	(3.697)	(0.318)	(0.297)	(0.0281)	(3.596)	(0.315)	(0.274)	(0.0270)
Post treatment	-1.616	0.0916	-0.372*	0.140*	1.518	0.000608	-0.167	0.176**
	(2.029)	(0.158)	(0.200)	(0.0757)	(1.839)	(0.126)	(0.204)	(0.0696)
Treatment X Post	-7.723**	-0.180	-0.429	-0.0496	-2.642	-0.0362	0.252	0.00789
	(3.634)	(0.245)	(0.367)	(0.0834)	(2.657)	(0.350)	(0.327)	(0.119)
Observations	708	658	649	708	830	759	781	830
R-squared	0.033	0.008	0.033	0.068	0.017	0.000	0.004	0.127

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from one-to-one matching - each treated unit is matched to one control unit, and matching is restricted to the area of common support. Additionally, control units are not reused.

Table I.22: Nearest neighbour matching

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	9.288***	0.0302	0.270	-0.0147	7.107**	0.309	-0.110	-0.0305
	(2.921)	(0.335)	(0.349)	(0.0446)	(3.414)	(0.325)	(0.319)	(0.0401)
Post treatment	-4.038	-0.184	-0.632***	0.128	3.307	0.141	-0.258	0.153*
	(3.016)	(0.265)	(0.227)	(0.105)	(3.096)	(0.197)	(0.275)	(0.0818)
Treatment X Post	-7.690*	-0.113	-0.184	-0.0355	-5.380	-0.271	0.275	0.0385
	(3.949)	(0.362)	(0.423)	(0.111)	(3.452)	(0.403)	(0.388)	(0.131)
Observations	531	531	531	531	586	586	586	586
R-squared	0.090	0.006	0.054	0.058	0.023	0.004	0.003	0.107

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from nearest neighbour matching - each treated unit is matched to two of its closest control observations, while only falling within the region of common support.

Table I.23: Radius matching

	2016				2019			
Dependent variables	**FCS**	**Assets**	**Exp.**	**Total loss**	**FCS**	**Assets**	**Exp.**	**Total loss**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	1.994	-0.328	-0.415	0.00289	2.140	-0.290	-0.488	0.00451
	(2.579)	(0.324)	(0.363)	(0.0283)	(2.822)	(0.318)	(0.317)	(0.0265)
Post treatment	-3.293**	0.168*	-0.0453	0.0838*	-1.387	0.191**	-0.0535	0.105***
	(1.297)	(0.0966)	(0.134)	(0.0472)	(1.281)	(0.0828)	(0.113)	(0.0365)
Treatment X Post	-8.121**	-0.174	-0.772*	0.00598	-2.907*	-0.234	0.102	0.0926
	(3.406)	(0.265)	(0.386)	(0.0569)	(1.701)	(0.318)	(0.321)	(0.108)
Observations	1,736	1,694	1,661	1,736	2,094	2,013	1,999	2,094
R-squared	0.056	0.015	0.072	0.058	0.009	0.014	0.016	0.148

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: Did estimation with weights from radius matching (common radius caliper (0.2) - each treated unit is matched to every control observation whose propensity score lies within a distance of 0.2, provided common support is satisfied.

J Treatment effect on firewood collection time

Table J.1: Treatment effect on hours spent collecting firewood

Dependent variable	Firewood collection	
	2016	**2019**
	(1)	(2)
Treatment	-0.343	-0.493
	(0.219)	(0.309)
Post treatment	-0.0208	-0.0305
	(0.179)	(0.256)
Treatment effect	0.00893	0.217
	(0.253)	(0.370)
Observations	1,150	1,490
R-squared	0.017	0.015

Robust standard errors in parentheses clustered at the EA level.
*** p<0.01, ** p<0.05, * p<0.1.
Notes: The estimation uses kernel-matching weights. The dependent variable measures the total number of hours the household spent collecting firewood on the day preceding the survey.

K Non-food expenditures & resource dependence

Table K.1: Non-food expenditures & resource dependence - 2016 sample

Non-food exp. (log) by resource dependence			
	Obs.	**Mean**	**Sd.**
Resource dependent	2,538	4.307	1.511
Not resource dependent	2110	5.263	1.673

Notes: Mean logged value of non-food expenditures over the past week by households' level of resource dependence in 2010, using the 2016 sample. Resource-dependent households are those whose livelihoods rely on agriculture and/or fuelwood collection. In contrast, non-resource-dependent households engage in alternative labour activities, including wage labour, non-agricultural work, and/or ganyu labour.

Table K.2: Non-food expenditures & resource dependence - 2019 sample

Non-food exp. (log) by resource dependence			
	Obs.	**Mean**	**Sd.**
Resource dependent	3,677	4.359	4.354
Not resource dependent	3,072	5.284	1.644

Notes: Mean logged value of non-food expenditures over the past week by households' level of resource dependence in 2010, using the 2016 sample. Resource-dependent households are those whose livelihoods rely on agriculture and/or fuelwood collection. In contrast, non-resource-dependent households engage in alternative labour activities, including wage labour, non-agricultural work, and/or ganyu labour.