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**Public Works Programmes:
Review of their effectiveness and empirical essays on their
contribution to climate resilience and social cohesion**

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Abstract

Poverty, underemployment, lack of infrastructure, low agricultural productivity, degradation of natural resources, climate change, and eroding social cohesion are among the biggest challenges that many low and lower-middle income countries are facing. Objectives linked to addressing these pressing challenges have been ascribed to public works programmes (PWPs). These are social protection instruments which offer remuneration (in cash or kind) for vulnerable people in exchange for temporary work on labour-intensive low-skill activities with social benefits. PWPs are being implemented in around two out of three developing countries. Given the substantial amounts spent on PWPs, it is critical to know to what extent the expectations towards them are backed by evidence. This dissertation sheds light on this overarching question with three self-contained essays. The first essay synthesises the evidence from PWPs in Sub-Saharan Africa, guided by three questions: First, what can we infer from the available impact evaluations regarding the effectiveness of PWPs as a social protection instrument? Second, what do we know about the role of the wage vector, asset vector, and skills vector in this respect? Third, what can we infer about the role of design features in explaining differences in outcomes? The other two essays use empirical evidence from Malawi to address more specific questions regarding the potential of PWPs to strengthen climate resilience and the relationship between PWPs and social cohesion.

What sets the evidence synthesis in my first essay apart from existing reviews of PWPs is that it accounts for their heterogeneity by systematically differentiating results by PWP type and outcome area (income, consumption and expenditures, labour supply, food security, nutrition, asset holdings, agricultural production and techniques, and education). Programmes that offer short-term ad-hoc employment (Type 1) are distinguished from programmes that offer more predictable employment over longer periods (Type 2). For the review of impacts, this paper relies solely on (quasi-)experimental studies, but for the analysis of the role of design factors also on other literature. In line with existing reviews, my results suggest that Type 1 programmes can effectively enable consumption smoothing in the wake of acute crises, whereas in contexts of chronic poverty, Type 2 programmes perform, on balance, better. Offering complementary access to extension services in Type 2 programmes can boost impacts further. However, in all cases, evidence is too scant and mixed to safely conclude whether the higher benefits of costlier PWP types justify the cost premium.

The second essay investigates the potential of PWPs to strengthen climate resilience. Among the main social protection instruments, the biggest potential to strengthen climate resilience is

often ascribed to PWPs if they create climate-smart community assets and transfer knowledge of climate-smart practices. Yet, there is a lack of evidence whether design changes to this end can indeed enhance the contribution of an existing PWP to climate resilience. I use a difference-in-differences approach based on two-period panel data to analyse how a modified PWP model performs compared to the standard model of Malawi's largest PWP after 24 months. The key modification is to embed public works in a communal watershed management plan with a strong emphasis on collective action and capacity building. I find that the modified approach considerably increased communal watershed management activities through voluntary labour contributions on top of the paid public works labour. While this increase was mainly driven by PWP participants, non-participants also made substantial contributions. I also find a small increase in the adoption of soil and water conservation practices on respondents' private land, especially by non-PWP participants. These findings imply that such modest changes can make PWPs climate-smarter. In particular, they can broaden the engagement in and adoption of climate-smart activities beyond the group of PWP participants.

The co-authored third essay investigates the relationship between Malawi's MASAF PWP and social cohesion, specifically within-community cooperation for the common good. Like the existing studies, we face the challenge that neither the assignment of the programme to communities nor the selection of individual participants is randomised. We try to mitigate the endogeneity concerns by triangulating fixed effects panel analyses for a set of outcomes and sectors using two datasets with different units of analysis (households and communities). We find that public works are positively associated with coordination activities and voluntary (unpaid) contributions to public goods, along both vertical ties (between community members and local leaders) and horizontal ties (among community members). Especially for school-building activities, voluntary inputs in the form of labour and other in-kind contributions are higher in the presence of the public works programme. Our results contribute to a better understanding of the link between social protection programmes with community-driven features and social cohesion.

Overall, the findings of the three essays in this dissertation contribute to the knowledge base regarding effectiveness and potential of PWPs across a broad range of outcome areas. Specifically, they offer new insights how to harness the potential of PWP to strengthen climate resilience and into the seemingly positive relationship between PWPs and social cohesion. The findings can help researchers and policy makers who are interested specifically in PWPs or in any of the many objectives that can be pursued through PWPs.

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List of Abbreviations

CfW	Cash-for-work
DDD	Triple difference
DiD	Difference-in-differences
FE	Fixed effects
HH	Household
IFA	Input-for-Assets
IHS	Integrated Household Survey
ITT	Intention-to-treat
IV	Instrumental variable
MASAF	Malawi Social Action Fund
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
MWK	Malawi Kwacha
M4C	MASAF-4 Catchments
OLS	Ordinary least squares
PSNP	Productive Safety Net Programme
PW	Public works
PWP	Public works programme
SD	Standard deviation
SSA	Sub-Saharan Africa
TOT	Treatment-on-the-treated
2SLS	Two-stage least squares

1 Introduction

Poverty, underemployment, lack of infrastructure, low agricultural productivity, degradation of natural resources, climate change, and eroding social cohesion are among the biggest challenges that many low and lower-middle income countries are facing. Objectives linked to addressing these pressing challenges have been ascribed to public works programmes (PWPs). These are social protection instruments which offer remuneration (in cash or kind) for vulnerable people in exchange for temporary work on labour-intensive low-skill activities with social benefits. PWPs are being implemented in around two out of three developing countries (World Bank, 2018). Given the substantial amounts spent on PWPs, it is critical to know to what extent the expectations towards them are backed by evidence. This is the overarching question that this dissertation aims to shed light on with three-self-contained essays.

Before I describe the specific focus of the essays and their contributions, it is important to first convey a better sense of the diversity and complexity of PWPs. The dual objectives of alleviating un(der)employment while creating useful assets are their common denominator. To ensure that only people in need enrol into PWPs, wages are usually deliberately set below the market rate or at the level of the minimum wage. In the likely case that demand for programme access exceeds the available spots, self-targeting is complemented with rationing mechanisms or (informal) rotation (World Bank, 2018). Beyond this, PWPs vary widely in terms of scale, focus, ambition, design characteristics, and implementation contexts.

Many PWPs are implemented as short-term humanitarian interventions, often in fragile settings. Examples are the large-scale ‘cash-for-work’ programmes (as short-term PWPs are often called) that were implemented in Syria’s neighbourhood where millions of Syrian refugees had arrived in the wake of the Syrian civil war (GIZ, 2018a, 2018b; Loewe et al., 2020; Roy & Schmid, 2018). The influx of refugees aggravated the already existing excess labour supply in the host territories and overstrained the capacity of the existing infrastructure. The PWPs in the region aim to address both. Similar PWPs are found in Afghanistan, Guinea-Bissau, Liberia, Nepal, Rwanda, Sierra Leone, and Sudan (Harvey et al., 2010; Rosas & Sabarwal, 2016; Subbarao et al., 2013).

PWPs are also implemented as medium- to long-term instruments in contexts of wide-spread chronic poverty and (seasonal) underemployment. In rural Sub-Saharan Africa, for example, there is a substantial excess labour supply during most periods of the year, with the possible

exception of the peak cultivation periods (Dillon et al., 2019; Dillon & Barrett, 2017). At the same time, there is a constant need for improvements in infrastructure that is not addressed by the private sector, including activities that could absorb large quantities of low-skilled labour (Lakmeeharan et al., 2020). The flagship PWP of this kind is Ethiopia's Productive Safety Net Programme (PSNP) that was launched in 2005. It encouraged the implementation of similar programmes, e.g., in Rwanda, Tanzania, Mozambique and Uganda (Sengupta, 2019).

There are also rights-based PWPs which guarantee each household access to a certain amount of employment each year (*employment guarantees*). The most prominent example is India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) that was enacted in 2005. MGNREGA guarantees at least 100 days of wage employment to every rural household. Similar schemes exist in other South Asian countries, but in the rest of the world PWPs do not offer unrestricted on-demand access.

The focus of the remunerated work activities varies widely. In the past, most PWPs built classical infrastructure like roads. Nowadays, most PWPs that are implemented in a rural setting concentrate on strengthening agricultural productivity and climate resilience. For example, Ethiopia's PSNP, which concentrates on land rehabilitation, afforestation, and other environmental activities, has been referred to as 'the largest climate change adaptation programme in Africa' (European Commission, 2018). India's MNREGA gradually changed its focus, to the extent that 65% of programme expenditure must now be spent on natural resource management and water-related expenditure (McCord & Paul, 2019). Even within one PWP, there can be a broad range of work activities, as South Africa's Expanded Public Works Programme (EPWP) shows. Besides increasing the labour intensity of government-funded infrastructure projects, the EPWP offers employment opportunities related to the environment, culture, social work, and non-profit organisations (SAG, 2021). While most PWPs were and still are implemented in rural settings, there has also been a proliferation of (semi-)urban PWPs like the Urban Productive Safety Net Programme (UPSNP) in Ethiopia, the Urban Cash for Work Programme (UCWP) in Uganda, and the *Travaux à Haute Intensité de Main-d'œuvre* (THIMO) programme in Côte d'Ivoire.

Some PWPs link the core component (remuneration in exchange for work) with complementary measures, for example, by promoting access to savings groups, loans, training, or (agricultural) extension services. Ethiopia's PSNP is complemented by the Household Asset Building Programme (HABP) that offers agricultural services. Beneficiaries of Rwanda's Vision 2020

Umurenge Programme (VUP) are linked to financial services (Gahamanyi & Kettlewell, 2015; Pavanello et al., 2017). THIMO in Cote d'Ivoire offers two forms of complementary training to facilitate a transition into self-employment or wage employment, respectively (Bertrand et al., 2016, 2017, 2021).

In response to the increasing intensity and frequency of environmental shocks, there have been wide-spread efforts in recent years to make social protection programmes, including PWPs, more 'shock-responsive' or 'adaptive' (Baez et al., 2019; Bowen et al., 2020; Davies et al., 2008; Longhurst & Sabates-Wheeler, 2019). This is done, for example, by building mechanisms into the programmes that enable rapid expansion of coverage to non-participants (horizontal expansion) and top-ups for existing programme participants (vertical expansion) in the wake of covariant shocks. In doing so, digital tools and processes have become increasingly important. The COVID-19 pandemic further accelerated these dynamics.²

This non-exhaustive overview of the diversity and complexity of PWPs shows that it is already a daunting task to comprehensively analyse a specific PWP. It also highlights that caution is required when applying lessons from one programme (context) to another in the quest to address the overarching question to what extent PWPs are effective in achieving the numerous objectives ascribed to them. Given that this dissertation sets out to address some of the knowledge gaps linked to this overarching question, it is important to bear this in mind. The first essay synthesises the evidence from PWPs in Sub-Saharan Africa, guided by two questions: First, what can we infer from the available impact evaluations regarding the effectiveness of PWPs as a social protection instrument? Second, what can we infer from the literature about the role of design features in explaining differences in outcomes? The other two essays use empirical evidence from Malawi to address more specific questions regarding the potential of PWPs to strengthen climate resilience (Chapter 3) and the relationship between PWPs and social cohesion (Chapter 4).

To structure the analysis of PWPs, I follow the framework by McCord (2012) which clusters the numerous potential impact mechanisms of PWPs into three vectors, namely the wages paid, assets created, and skills conveyed. The wage vector subsumes mechanisms that are linked to the wage that is paid for working in a PWP, including its potential insurance function in the

² The patterns, methods, and lessons of the COVID-19 response have been captured in numerous practitioner-oriented publications (Beazley et al., 2021; Gentilini et al., 2021; Lowe et al., 2021).

event of shocks and general equilibrium effects through the income injection into the (local) economy. The asset vector comprises of mechanisms linked to the infrastructure created or services provided through PWP, including the social interactions that take place during the work activities or are fostered by them. The skills vector includes all forms of learning and work experience in the context of PWP, namely on-the-job (learning-by-doing) or off-the-job (directly or indirectly). Off-the-job training can be linked to the work activities or focus on more general complementary skills. It can also be open to non-PWP participants. Indirect benefits may arise when non-PWP participants observe and learn from PWP participants.

Like most existing studies of PWP, I analyse them from a social protection perspective. Social protection, as I use the term in this dissertation, comprises ‘all public and private initiatives that provide income or consumption transfers to the poor, protect the vulnerable against livelihood risks, and enhance the social status and rights of the marginalised; with the overall objective of reducing the economic and social vulnerability of poor, vulnerable and marginalised groups’ (Devereux & Sabates-Wheeler, 2004).

There have been several ambitious efforts to summarise the knowledge base on PWP as a social protection instrument in the recent (del Ninno et al., 2009; Gehrke & Hartwig, 2018; Lal et al., 2010; McCord, 2012; Subbarao et al., 2013) and not so recent past (von Braun, 1991). Often, PWP have also been included in reviews of transfer-based social protection instruments which, besides PWP, also comprises (conditional and unconditional) cash transfer programmes (Arnold et al., 2011; Hidrobo et al., 2018). My evidence synthesis complements the existing reviews as follows: I systematically account for heterogeneity by differentiating results by PWP type for a wide range of outcome areas, focus on Sub-Saharan Africa, and rely solely on (quasi-)experimental studies for the review of impacts.

The existing literature on the linkage of PWP and climate resilience concentrates on the benefits, potential, and limitations of PWP in this respect. (Adam, 2015; Andersson et al., 2011; Esteves et al., 2013; Fischer, 2019; Gazeaud & Stéphane, 2020; Godfrey-Wood & Flower, 2018; Ignaciuk et al., 2021; Kaur et al., 2019; Ravindranath et al., 2013; Steinbach et al., 2016; Weldegebriel & Prowse, 2013; Woolf et al., 2018). To the best of my knowledge, my essay in Chapter 3 is the first attempt to use a counterfactual design to investigate whether design changes to enhance the contribution of an existing PWP to climate resilience succeeded in doing so. I use a difference-in-differences approach based on two-period panel data to

analyse how a modified PWP model performs compared to the standard model of Malawi's largest PWP, the Malawi Social Action Fund (MASAF) PWP.

The co-authored essay in Chapter 4 explores the relationship between PWPs and social cohesion in a case study of the same MASAF PWP in Malawi. In the only other quantitative study on the issue that we are aware of (Bhuwania et al., 2016), endogeneity concerns prevent a rigorous identification of causal PWP effects on social capital because neither the assignment of the programme (MNREGA in their case) to communities nor the selection of individual participants is random. In the essay in Chapter 4 we face the same challenge but try to mitigate it by triangulating fixed effects panel analyses for a set of outcomes and sectors using two datasets with different units of analysis (households and communities). In what follows, I describe the respective contributions of the three essays in more detail.³

1.1 Contributions of Chapter 2: Review of the evidence from public works programmes in Sub-Saharan Africa

The essay in Chapter 2 is an evidence synthesis of the impacts of PWPs and the design factors that explain them. As mentioned before, PWPs are diverse in terms of design, objectives, and implementation contexts and they can potentially have impacts on many outcome areas through numerous channels. To do justice to this complexity and to set my review apart from existing reviews of PWPs, I focus only on Sub-Saharan Africa and account for heterogeneity by differentiating results by PWP type and outcome area. Programmes that offer short-term ad-hoc employment (Type 1) are distinguished from programmes that offer more predictable employment over longer periods (Type 2). Because Ethiopia's PSNP is the only Type 2 programme in the region, I effectively compare the PSNP to several Type 1 programmes implemented in other countries and the Type 1 programmes in Ethiopia that preceded the PSNP in the region. The considered outcome areas are income, consumption and expenditures, labour supply, food security, nutrition, asset holdings, agricultural production and techniques, and education.

³ Because one of my essays is an evidence synthesis and the other two essays also discuss the literature relevant for their respective focus, I do not include an additional general literature review in the introduction of the dissertation.

For the review of impacts, I rely solely on (quasi-) experimental studies, but for the analysis of the role of design factors also on other literature. The results suggest that Type 1 programmes can effectively enable consumption smoothing in the wake of acute crises. In contexts of chronic poverty, the Type 2 programme perform, overall, better than the cheaper Type 1 programmes. Offering complementary access to extension services in Type 2 programmes can boost impacts further. However, in all cases, evidence is too scant and mixed to safely conclude whether the higher benefits of the costlier PWP types justify the cost premium. Regarding the comparison to alternative interventions, the paper concludes, in line with existing reviews, that PWPs (of any type) are only preferable if they are implemented well, the design fits the context, and there are substantial and lasting benefits from improved infrastructure or skills. Due to the evidence gaps, ascertaining this often relies on assumed benefits.

The essay adds to the literature on the effectiveness of transfer-based social protection instruments (Arnold et al., 2011; Bastagli et al., 2016, 2019), and to the related literature that focuses on the cost effectiveness of different poverty reduction instruments, including those that are not transfer-based (Blattman & Ralston, 2015; Fiszbein et al., 2014; McKenzie, 2017; Ravallion, 2018). Moreover, the essay contributes to the literature concerned with PWPs (Barrett et al., 2002; del Ninno et al., 2009; Gehrke & Hartwig, 2018; Lal et al., 2010; Lieuw-Kie-Song, 2011; McCord, 2012; Ravallion, 1999; Subbarao et al., 2013). Previous reviews drew on the small quantitative evidence base and complemented it variably with the qualitative, theoretical, conceptual and operational insights of academics, implementers and other practitioners. While there are arguably merits to this approach, it makes it difficult for readers to judge the internal and external validity of findings and ensuing policy implications. To address this problem, for its review of programme effectiveness, this paper relies solely on experimental and quasi-experimental studies that provide causal or nearly causal inference in reference to a (statistically constructed) comparable control group.

1.2 Contributions of Chapter 3: Climate smart(er) social protection: Evidence from public works in Malawi

Environmental shocks are among the major covariate risks to the welfare of people and climate change is expected to exacerbate them. This has sparked interest in understanding the contribution that PWPs can make specifically to strengthening climate resilience. The essay in

Chapter 3 focuses on this topic. There are already a number of insightful studies that highlight the benefits, potential, and limitations of PWPs in this respect (Adam, 2015; Andersson et al., 2011; Esteves et al., 2013; Fischer, 2019; Gazeaud & Stéphane, 2020; Godfrey-Wood & Flower, 2018; Kaur et al., 2019; Ravindranath et al., 2013; Steinbach et al., 2016; Weldegebriel & Prowse, 2013; Woolf et al., 2018). However, none of these studies compare empirically whether design changes to make existing programmes climate-smarter succeed in doing so. They also do not disentangle the role of and benefits for non-PWP participants. Moreover, quantitative studies from PWPs outside of India and Ethiopia do not seem to exist to date, with the notable exception of Ignaciuk et al. (2021). My essay addresses these gaps with empirical evidence from Malawi.

I use a difference-in-differences approach based on two-period panel data to analyse how a modified PWP model performs compared to the standard model of Malawi's largest PWP after 24 months. The key modification is to embed public works in a communal watershed management plan with a strong emphasis on collective action and capacity building. I find that the modified approach considerably increased communal watershed management activities through voluntary labour contributions on top of the paid PW labour. While this increase was mainly driven by PWP participants, non-participants also made substantial contributions. I also find a small increase in the adoption of soil and water conservation practices on respondents' private land, especially by non-PWP participants. These findings imply that such modest changes can make PWP climate-smarter. In particular, they can broaden the engagement in and adoption of climate-smart activities beyond the group of PWP participants.

In addition to the above-mentioned literature on the role of PWPs for strengthening climate resilience, the essay adds to the literature on collective action in the context of watershed management (Agrawal et al., 2015; Reichert, 2014; T. A. White & Runge, 1995), environmental conservation through payment for eco-system services schemes (Alix-Garcia et al., 2019; Neuteleers & Engelen, 2015; Popa, 2015; Rode et al., 2015), and social protection programmes (Adato, 2000; Attanasio et al., 2015; Evans et al., 2019; Loewe et al., 2020). Lastly, it contributes to the literature on technology adoption in the context of PWPs and/or communal watershed management (Gebremedhin & Swinton, 2003; Hagos & Holden, 2006; Ignaciuk et al., 2021).

1.3 Contributions of Chapter 4: Public works programmes and cooperation for the common good: Evidence from Malawi

Strong reciprocal relationships and joint community activities can serve as a cushion that insures people against shocks by providing mutual support during times of need. They are also important in the face of large collective challenges such as the COVID-19 pandemic, climate change, and scarcity of common resources. Social protection is one potential channel to build or maintain social cohesion. Most existing studies on this relationship concern cash transfer programmes, whereas PWP have so far received less attention. Yet, PWP are particularly promising for enhancing social cohesion because due to the work component they require a higher quantity and quality of interactions than other types of social protection. The few studies that investigate the relationship between PWP and social cohesion find positive associations with horizontal dimensions of social cohesion in the context of India's MGNREGA (Bhuwania et al., 2016) and for a cash-for-work programme in a refugee context in Jordan (Loewe et al., 2020). However, to the best of my knowledge, there are no quantitative studies that evaluate the effects of a PWP on any of the attributes or dimensions of social cohesion in the African context; especially none that investigate the relationship between public works and cooperation for the common good outside the framework of the PWP.

The essay in Chapter 4, co-authored with Marina Dodlova, addresses this gap by investigating the relationship between Malawi's largest and oldest social protection programme, the MASAF PWP, and social cohesion. We use the conceptualisation by Burchi et al. (forthcoming) that distinguishes three attributes of social cohesion: cooperation for the common good, inclusive identity, and trust. In this paper, we focus on the first attribute, specifically on *within-community coordination*, measured by meeting activities, and *voluntary contributions to local public goods* (in the form of unpaid labour, materials, or other in-kind contributions). As in the existing studies, endogeneity concerns prevent a rigorous identification of causal PWP effects on social capital because neither the assignment of the MASAF PWP to communities nor the enrolment of households in the programme is randomised. As a second-best approach, we triangulate correlational results of fixed effects panel analyses for a set of outcomes and sectors using two datasets with different units of analysis (households and communities).

We find a positive association between PWP and cooperation for the common good. The association is quite robust across different outcomes and samples. Specifically, we find that PWP are positively associated with overall coordination among community members as well

as top-down and bottom-up cooperation in specific sectors like agriculture, public transportation and bridges, school-building activities, and care. In the presence of PWPs, voluntary contributions are also higher in specific sectors, especially for school-building activities where we find a positive association in both samples (i.e., both at the household and community level). Our results contribute to a better understanding of how social protection programmes with community-driven features are linked to social cohesion across sectors and along both horizontal and vertical lines in a developing country context, particularly in settings with a relatively homogenous population unaffected by violent conflict. Considering the similarities between PWPs and cash transfer programmes (Adato, 2000; Adato & Roopnaraine, 2004; Attanasio et al., 2015; Barca et al., 2015; Camacho, 2014; L. Cameron & Shah, 2014; Devereux et al., 2017; Evans et al., 2019; Kardan et al., 2010; Pavanello et al., 2016; Valli et al., 2019; Veras Soares et al., 2010) as well as community-driven development programmes (King et al., 2010; Nguyen & Rieger, 2017; Vajja & White, 2008; H. White et al., 2018), the essay also contributes to the literature on their respective relationship to social cohesion.

Overall, the findings of the three essays in this dissertation contribute to the knowledge base regarding effectiveness and potential of PWPs across a broad range of outcome areas. Specifically, they offer new insights how to harness the potential of PWP to strengthen climate resilience through modest design changes and into the seemingly positive relationship between PWPs and social cohesion. The findings can help researchers and policy makers who are interested specifically in PWPs or in any of the many objectives that can be pursued through PWPs.

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2 Review of the evidence from public works programmes in low and lower-middle income countries in Sub-Saharan Africa

2.1 Introduction

Public works programmes (PWP) are social protection instruments that offer remuneration (in cash or kind) for vulnerable people in exchange for temporary work on community activities. They are popular among governments and donors in developing countries. Around two-thirds of developing countries have at least one PWP (World Bank, 2018). Often, a substantial share of total social safety net expenditures is spent on them. Their main appeal lies in their expected *double dividend*. In addition to immediate welfare benefits to those employed, they are also assumed to positively contribute to both household productivity and broader economic growth. The work is purported to convey skills that may improve participants' employability or capabilities which boost income from self-employment, and to create assets, in particular infrastructure (McCord, 2012). Moreover, PWPs may serve as an insurance whose effectiveness depends on the predictability and duration of the work.

Beyond their commonalities, PWPs differ in their prioritization of objectives, the exact programme design and implementation contexts. Some are straightforwardly based on a self-targeting mechanism, while others rely on more complex targeting mechanisms or are linked to complementary measures. Some are implemented as a short-term emergency response to acute crises, for example, in (post-) conflict settings or after natural disasters, others as more long-term responses to wide-spread chronic poverty and almost perennial underemployment. Furthermore, some programmes have an urban focus, others a rural focus. These differences in the implementation context have important implications for programming and expected benefits (del Ninno et al., 2009; Gehrke & Hartwig, 2018; McCord, 2005, 2008; Ravallion, 2018; Subbarao et al., 2013).

The main aim of this paper is to synthesise what we know about the impacts of PWPs in Sub-Saharan Africa in a way that accounts for this heterogeneity. This paper complements the recent review by Gehrke and Hartwig (2018) in several respects. First, it proposes a typology of

different types of PWP and uses this typology throughout the review. Second, this review considers a larger range of potential outcomes, i.e., it concentrates not only on the impact on productive outcomes such as productive asset holdings, agricultural production and technology adoption, but considers also consumption, food security, nutrition, education and ownership of durable consumption goods. Third, this study adds a qualitative analysis of the optimal design factors of PWP by analysing how different design features alter outcomes. Unlike Gehrke and Hartwig (2018), this paper focuses exclusively on programmes implemented in Sub-Saharan Africa to account for their context dependency.

Several different typologies of PWP are found in the literature (Gehrke & Hartwig, 2018; McCord, 2012; Subbarao et al., 2013), but none of them fully fits the purpose of this paper. A typology has therefore been developed that adapts and combines aspects of existing ones. It differentiates programmes with a short-term focus (Type 1) from programmes with a medium to long-term focus (Type 2). The key difference concerns the duration, continuity and predictability of the employment offered to individual participants. If the employment is complemented (e.g., by training or by access to credit or extension services), the programme is classified as Type 1 Plus or Type 2 Plus respectively.

Like Gehrke and Hartwig (2018), this paper adds to the literature on the effectiveness of transfer-based social protection instruments (Arnold et al., 2011; Bastagli et al., 2016, 2019), and to the related literature that focuses on the cost effectiveness of different poverty reduction instruments, including those that are not transfer-based (Blattman & Ralston, 2015; Fiszbein et al., 2014; McKenzie, 2017; Ravallion, 2018). Moreover, the paper contributes to the literature concerned with PWP (Barrett et al., 2002; del Ninno et al., 2009; Gehrke & Hartwig, 2018; Lal et al., 2010; Lieuw-Kie-Song, 2011; McCord, 2012; Ravallion, 1999; Subbarao et al., 2013). Previous reviews drew on the small quantitative evidence base and complemented it variably with the qualitative, theoretical, conceptual and operational insights of academics, implementers and other practitioners. While there are evident merits to this approach, it makes it difficult for readers to judge the internal and external validity of findings and ensuing policy implications. To address this issue, this paper relies for its review of programme effectiveness solely on experimental and quasi-experimental studies that provide causal or nearly causal inference in reference to a (statistically constructed) comparable control group. All Type 1 (Plus) and Type 2 (Plus) programmes in low and lower-middle income countries in Sub-

Saharan Africa are considered as long as they are targeted at the poor and vulnerable and, hence, have an explicit social protection objective.

In order to find all studies that satisfy the inclusion criteria, a rigorous search method was applied. Ultimately, 27 studies from six countries remained. An important limitation of this paper is that all but five studies relate to Ethiopia. The other five relate to Côte d'Ivoire, Ghana, Malawi, Sierra Leone, and Rwanda. Except for Ethiopia's Productive Safety Net Programme (PSNP), all analysed studies are Type 1 (Plus) programmes. For the qualitative analysis of the drivers of programme effectiveness, the evidence from the experimental and quasi-experimental studies is complemented with observational and qualitative evidence, and some theoretical considerations, to allow for investigating 'softer' and non-quantifiable factors that are not properly captured in quantitative studies.

The results suggest that Type 1 programmes can effectively enable consumption smoothing in the wake of acute crises. In contexts of chronic poverty, Type 2 programmes perform, on balance, somewhat better than the cheaper Type 1 programmes. Offering complementary access to extension services in Type 2 programmes can boost impacts further. However, evidence is too scant and mixed to safely conclude whether the marginally higher benefits of the costlier PWP types justify the cost premium. Regarding the comparison to alternative interventions such as cash transfer programmes, the paper concludes, in line with existing reviews, that PWPs (of any type) are only preferable if there is adequate institutional capacity to implement this complex intervention well, the design fits the context, and there are substantial and lasting benefits from improved infrastructure or skills. Due to the evidence gaps, ascertaining this often relies on assumed benefits.

The remainder of this article is structured as follows. The next section defines PWPs and suggests a new typology. Section 3 discusses the theory of change underlying PWPs. Section 4 outlines the inclusion criteria and search strategy applied in the review and provides the list of included studies. Section 5 describes the method used for synthesising the evidence. Section 6 reviews programme impacts. Section 7 discusses factors that drive programme effectiveness. Section 8 concludes.

2.2 Definition and typology of PWPs

There are many different names for what I refer to as PWPs in this paper (e.g., labour-intensive employment programmes, cash-/food-/input-for-work, and workfare). They all denote social protection interventions that offer remuneration (in cash or kind) to poor or vulnerable people in exchange for temporary work on labour-intensive community projects which generate or maintain (public) infrastructure and social services (McCord, 2012; Subbarao et al., 2013). Beyond this common denominator, they differ widely. To account for this heterogeneity in a way that best serves the purpose of this paper, I propose a typology of PWPs that adapts and combines aspects of other typologies found in the literature (Gehrke & Hartwig, 2018; McCord, 2012; Subbarao et al., 2013). The main difference is how our typology distinguishes programmes along two dimensions. The first dimension concerns the duration, continuity and predictability of the employment offered to individual participants. The second dimension accounts for additional measures that complement the public works (PW) employment.

The first dimension classifies programmes as Type 1 if they have a short-term focus or as Type 2 if they have a medium to long-term focus. More precisely, in Type 1 programmes, targeting is ad-hoc, often based on a self-targeting mechanism by deliberately setting the wage rate low, and re-targeting is frequent. As a result, there is typically considerable movement of people in and out of the programme from one work cycle to the next, and predictability of access is low. Type 1 programmes are mostly implemented in contexts of acute crisis to enable short-term consumption smoothing. However, especially in the past, they were often also implemented in contexts of chronic poverty (McCord, 2012). Type 2 programmes, on the other hand, are mostly implemented in contexts of wide-spread chronic poverty. They have a medium to long-term focus in the sense that they place strong emphasis on keeping initially targeted households on the programme for several years to allow for the accumulation of savings and assets in order to proactively protect against risks and to strengthen livelihoods. Therefore, continuity and predictability are higher. Targeting is typically done through wealth ranking because pure self-targeting through a low wage rate stands at odds with the objectives of these programmes. Some Type 2 programmes have an additional emergency component that allows a temporary scale-up of the programmes to cover households affected by acute shocks.

The second dimension refers to whether programmes offer extra measures aimed at enhancing and sustaining impacts in addition to the PW job (e.g., by promoting access to savings groups, loans, insurance, training, or various kinds of extension services). In principle, complementary

measures can be attached to both types of programmes. However, in practice, they are mostly found in programmes that are closer to the Type 2 end of the continuum. Henceforth, I will refer to a Type 1 programme with such extras as *Type 1 Plus* and a Type 2 programme with extras as *Type 2 Plus*. The typology is summarised in Table 2.1.⁴

Table 2.1: Typology of PWPs

	Key design feature	Primary objective	Example(s)
Type 1	Single short-term episode of employment	To enable consumption smoothing	Most past PWPs that were supported through social action funds in Africa, e.g., Malawi's MASAF III PWP Most emergency PWPs, e.g., YESP/CfW in Sierra Leone
Type 2	Repeated or ongoing employment	To provide a form of income insurance	Ethiopia's PSNP
... Plus	Additional measures complement the PW employment, e.g., training, or access to credit or extension services	Varies, but usually to enhance or sustain the gains of the PW employment in order to offer a path out of poverty	Côte d'Ivoire's PEJEDEC-THIMO + training (Type 1 Plus) Ethiopia's PSNP + HARP/OFSP (Type 2 Plus)

Notes: This typology is adapted from Gehrke & Hartwig (2015), McCord (2012), McCord (2008) and Subbarao et al. (2013). MASAF III is the PWP under the third phase of the *Malawi Social Action Fund*. YESP/CfW is the *Cash for Work* component of the *Youth Employment Social Support Project*. PSNP is the *Productive Safety Net Programme*, HARP the *Household Asset Building Programme* and OFSP the *Other Food Security Programme*. PEJEDEC-THIMO denotes the *Labour-Intensive Public Works* component of the *Emergency Youth Employment and Skills Development Project*.

2.3 Theory of change of PWPs

PWPs are expected to yield a range of positive impacts through three main vectors: a wage, skills, and asset vector (McCord, 2012). The relative importance of the vectors, the specific mechanisms at play in each vector, and their interactions with other factors vary per context and programme. Note that *short-term* impacts in this paper refer to the first two years on the programme. *Medium-term* impacts refer to more than two years on the programme (only applicable for Type 2) or shortly after the end of programme participation (≤ 1 year). *Long-term* impacts refer to periods well after the end of programme participation (> 1 year).

2.3.1 Wage vector

The wage vector subsumes mechanisms that are directly linked to the wage that is paid for working in a PWP. The actual value of the PWP income may differ between households. As a

⁴ India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) does not fall into any category in this typology because, unlike Type 2, it offers high predictability by offering recurrent unrationed access on demand. Its duration, in terms of programme lifespan and workdays per person per year (up to 100), far exceeds what Type 1 offers.

first step to account for this, the wage rate must be put in relation to the number of workdays and working hours per day. Type 2 PWPs typically transfer higher total transfer values than Type 1 PWPs. Furthermore, due to the labour requirement, PWPs, unlike cash transfer programmes, may entail opportunity costs for the household that result in reduced income from other income sources (Datt & Ravallion, 1994; Ravallion, 1990, 1991, 1999; Ravallion & Jalan, 1999) or non-monetary time trade-offs.⁵ Third, the purchasing power of wages paid in cash may quickly erode, especially in crisis situations, and the relative attractiveness of payment in kind versus payment in cash may increase in such cases. This is particularly relevant in the context of Type 1 PWPs that offer work, and thus payment, mainly during acute crises. These aspects are summarised in the following schematic equation, although the role of inflation is left implicit:

$$\begin{aligned} \text{Total transfer value} = & \quad (\text{daily wage rate} * \# \text{ of total workdays}) \\ & - \text{forfeited total income from other sources} \end{aligned}$$

Furthermore, the magnitude of expected impacts typically depends on how the total transfer value compares to the socio-economic situation of the household. The underlying question is what the transfer enables the household to do that it would otherwise not be able to. One way to account for this is to put the transfer value in relation to the household poverty gap (McCord, 2012). The ensuing ratio is denoted as *transfer share*:⁶

$$\text{Transfer share} = \text{total transfer value} / \text{household poverty gap}$$

The household poverty gap is a measure of the depth of poverty that captures how far the consumption of a household falls short of the poverty line. For the purposes of this paper, the poverty line constitutes a threshold below which households fail to save and make productive investments because their immediate priority is to meet basic needs. By dividing the transfer value by the household poverty gap, the transfer share also accounts for changes in the purchasing power of the transfer value. The household-specific transfer share shapes the decision on how the PWP income is used and, thus, the specific programme effects through the wage vector. Other factors that matter in this respect are household (risk) preferences, the timing of the work cycles, and predictability (discussed below). For example, if a PWP targets food-

⁵ Unless households deliberately decide to decrease their income in order to qualify for such a transfer programme. Instead of opportunity costs, Ravallion uses the term ‘foregone earnings’ in his seminal papers on PWPs (which concentrate empirically mostly on Latin America and South Asia). I deliberately use the term opportunity costs to emphasise that I also consider non-monetary costs.

⁶ Adapted from terminology often used in the work of the Transfer Project on cash transfer programmes in Sub-Saharan Africa.

insecure households in acute times of need, one would expect stabilising food consumption to be the first spending priority of most households. In normal times, the spending priorities are likely to be more heterogeneous. Generally, unless the poverty gap is fully closed, productive and promotive impacts through the wage vector are unlikely due to the limited scope for accumulation and investment (Devereux & Sabates-Wheeler, 2004). If the transfer share is small, even protective impacts may fall short of expectations.

Furthermore, employment in a PWP may fulfil an insurance function. Its effectiveness depends not only on the transfer share but also on how well a household can predict whether, when and for how long it can access the PWP. The effectiveness of the insurance function, in turn, may influence the saving behaviour and risk management of households. In both cases, there is no clear expectation regarding the direction of the effect. On the one hand, predictable access ‘may reduce the need for precautionary savings’ (Andersson et al., 2011). On the other hand, the PWP may enable those households to save or access loans which would not have been able to do so otherwise. Temporary income security may also encourage some households to make riskier investments with high payoff potential in the medium-term. There is some evidence for this mechanism relating to the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) of India (Gehrke, 2017; Zimmermann, 2014). However, I cannot rule out that income security leads to a reduction in investment elsewhere due to a lower sense of urgency to improve one’s situation. Lastly, positive general equilibrium effects on private sector wages are detected in the context of the large-scale MGNREGA programme (Azam, 2012; Berg et al., 2012; Imbert & Papp, 2015; Muralidharan et al., 2018; Zimmermann, 2014), but such effects are less likely for smaller programmes.

2.3.2 Asset vector

What sets PWPs most clearly apart from cash transfer programmes is the possibility that benefits accrue not only from the transfer but also from the assets created or services provided. Depending on the type of asset or service, the expectation is that they generate income opportunities for participants and their communities, shield participants and their communities from the negative effects of shocks such as floods and droughts, or improve the quality of, or access to, social services. To what extent the impacts through the asset vector materialise depends on many factors that are further discussed in Section 2.7.3.

2.3.3 Skills vector

Given that skills transfer is not an explicit objective of many PWPs, the skills vector often plays a minor role in the literature about PWPs. Exceptions are Gehrke and Hartwig (2018) and McCord (2012). There are three main channels through which skills may be imparted to PWP participants: first, learning-by-doing through participation in the regular PWP activities, second, more elaborate on-the-job training closely linked to the regular PWP activities, and, third, complementary off-the-job training that is relatively or fully detached from the regular PWP activities, but primarily targeted at PWP participants. The conveyed skills can range from soft, to technical, to business skills (Blattman & Ralston, 2015). In principle, benefits that arise from the application of newly learned or upgraded skills may manifest themselves either in the form of improved market-based employment prospects (higher employability), or through a sustained increase in income from self-employed micro-entrepreneurial activities or on-farm activities.

2.3.4 Interactions of the mechanisms at play in the three vectors

The mechanisms underlying the three vectors may affect many outcomes directly or indirectly. The theory of change of PWPs is summarised in Figure 2.1.⁷ The relative importance of the mechanisms, their interactions and, ultimately, the likelihood and expected magnitude of the effects varies depending on the PWP type, the implementation context and household characteristics.

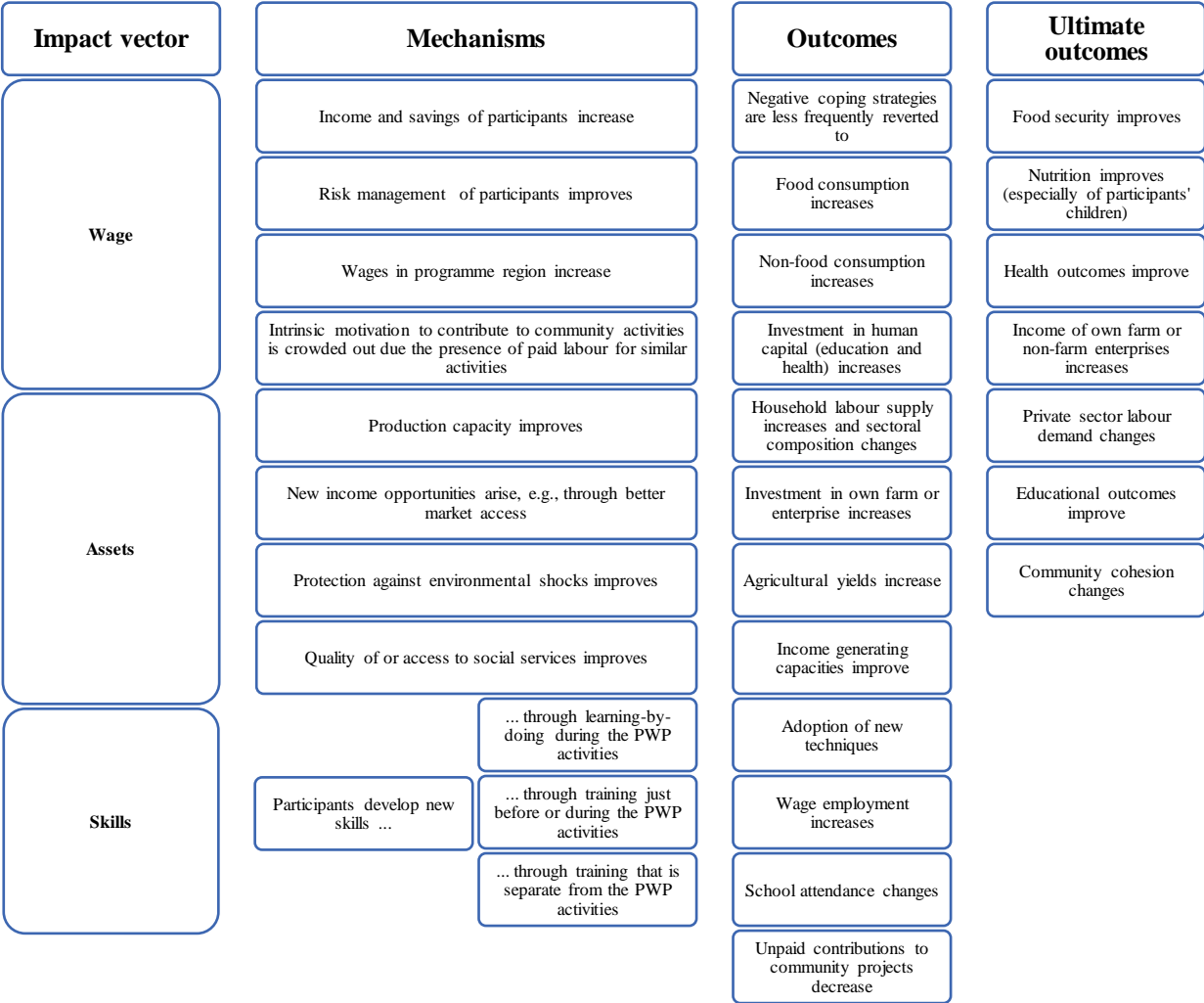
In short, it is expected that tangible short-term benefits are mainly driven by mechanisms in the wage vector although some assets or skills may also have immediate benefits. The mechanisms in the asset vector and skills vector are critical when it comes to generating durable longer-term benefits. Regarding interactions between mechanisms, the best-case scenario is a virtuous cycle driven by the productive effects that Gehrke and Hartwig (2018) concentrate on. However, a lot of conditions must be met for this to happen. This also applies to many other effects. Many pitfalls may undermine expected impacts because getting the design and implementation of PWPs right is administratively demanding.

⁷ For the sake of simplicity, the figure assumes that payment is in cash although the depiction would not change much if payment was in kind. Ultimate outcomes denote outcomes that require various intermediate outcomes or significant time before they materialize. Some effects primarily concern PWP participants, whereas others concern the wider community or specific groups therein.

In some outcome areas, the direction of the effects is difficult to predict theoretically because there are potential mechanisms that work in opposite directions. This applies particularly to labour supply (Gehrke & Hartwig, 2018) and child-level outcomes such as child labour and education (Favara et al., 2019). Here, the likelihood of negative effects outweighing the positive ones is highest for labour-constrained households because their (non-monetary) opportunity costs are high.

If applying skills in business activities requires seed capital, the combined benefits of the wage and asset vector must allow for the required asset accumulation or access to credit at reasonable conditions. The latter may be facilitated through complementary programme components or other linkages.

Figure 2.1: The theory of change of PWPs



Notes: This figure is based on Gehrke & Hartwig (2018) but has been expanded by author.

As a consequence of the shift towards environmental activities in many PWPs, the literature about payments for ecosystem services becomes increasingly relevant for understanding the motivational and community-level effects of PWPs. Findings from this literature imply that interactions across vectors can be more ambiguous than the literature on PWPs, in which these effects have received little attention, suggests. There is a growing body of empirical evidence that monetary incentives may crowd out intrinsic motivation to engage in ecosystem conservation, although it is not yet well understood when and under what conditions (Neuteleers & Engelen, 2015; Popa, 2015; Rode et al., 2015). *A priori*, it cannot be ruled out that crowding out of unpaid community activities takes place in the context of PWPs, especially if the PWPs focus on activities that are also undertaken by community members without payment. If this is indeed the case, it would weaken a major argument in favour of PWPs vis-à-vis regular cash transfer programmes, namely that they create additional community assets.

2.4 Inclusion criteria, search strategy and search results

2.4.1 Inclusion criteria

As argued above, the implementation context of PWPs matters immensely. To avoid undue generalization across contexts, I restricted the search for relevant programmes to Sub-Saharan Africa, and within this region to low income and lower-middle income countries as classified in the World Bank list of economies from June 2017.⁸ The latter decision is based on the argument that differences in the administrative capacity of the state and in the level of development of the private sector of the economy limit the generalizability of experiences with PWPs in such countries compared to upper-middle and high income countries. As a result, PWPs in Botswana, Equatorial Guinea, Gabon, Mauritius, Namibia, Seychelles, and South Africa were excluded. In the remaining countries, all PWPs were considered that fit the definition and typology presented in Section 2.2, irrespective of whether they were implemented in rural or urban areas.

The methodological minimum standards were chosen such that I only included experimental or quasi-experimental studies that provided causal or nearly causal inference in reference to a (statistically constructed) comparable control group. I generally gave preference to peer-

⁸ Thus, the threshold for inclusion is a gross national income (GNI) per capita of less than \$3,956 in 2016 as calculated on the basis of the World Bank Atlas method. The threshold between low- and lower middle-income countries is \$1,005.

reviewed publications in academic journals if there were several versions of a study. However, evaluation reports and unpublished papers were also considered as they may reduce a potential publication bias and avoid the exclusion of recent evaluations. All potentially affected outcomes discussed in Section 2.3 were considered.

2.4.2 Search strategy

The search methods included the screening of electronic databases, relevant websites and scientific journals, as well as literature snowballing, and contacting key researchers and experts. The search line “‘impact’ or ‘evaluation’ or ‘assessment’” was combined with every single term in the following list in order to account for the many names for the types of interventions I am interested in: ‘public works’, ‘PWP’, ‘PW’, ‘public employment’, ‘labour-intensive employment’, ‘cash-for-work’, ‘input-for-work’, ‘inputs for work’, ‘IFW’, ‘input for asset’, ‘IFA’, ‘food-for-work’, ‘CFW’, ‘food for assets’, ‘FFA’, and ‘workfare’.

2.4.3 Search results

Table 2.2 lists all PWPs that are covered by the selected studies.⁹ Except for Ethiopia’s PSNP, all programmes are of Type 1. Two of those are also from Ethiopia and were implemented before the PSNP was launched. The High Value Food Basket (HVFB) variant of the PSNP was implemented in selected locations in the Amhara region. Instead of cash, PSNP participants in these locations received an HVFB with an imputed average value that exceeded the average value in the regular PSNP locations (Gilligan et al., 2009a). The Type 2 Plus variant of the PSNP is the combination of the regular PSNP component with the Other Food Security Programme (OFSP) or the Household Asset Building Programme (HABP) that eventually replaced the OFSP. Both aimed to facilitate asset accumulation through access to repeated transfers or services relevant to agriculture (Hoddinott et al., 2012). Some of the studies evaluating the PSNP compared the performance of additional programme variants, e.g., variations of the transfer value and sub-components of the OFSP/HABP.

Of the Type 1 PWPs, only the PEJEDEC-THIMO, which was implemented in a (semi-)urban context in Côte d’Ivoire, had a Plus component. Bertrand et al. (2016, 2017) compared the performance of non-participants to three different treatment groups (and the pooled treatment

⁹ Some interesting programmes with Plus components, such as the R4 Rural Resilience Initiative of the World Food Programme, are not reflected in this review because there is no evaluation of it that meets the inclusion criteria (Madajewicz et al., 2013).

group): Type 1 without complementary training, Type 1 Plus with self-employment training that conveyed basic entrepreneurship skills, and Type 1 Plus with wage-employment training that concentrated on job search skills. None of the other selected Type 1 PWP studies differentiated between the core PW component and complementary components. This being said, Beegle et al. (2017) explored complementarities between the MASAF III PWP and a separate fertiliser subsidy programme in Malawi. In addition, the study cross-randomised the timing of the second of two work cycles (pre-harvest vs. (post-)harvest) and the schedule of payments (lump-sum after twelve days vs. five equal instalments). Debela et al. (2017) did not explicitly differentiate between the PSNP (Type 2) and its predecessors (Type 1) so it is denoted as Type 1/2. The study differentiated payment modalities (food only, cash only and mixed).

Table 2.2: List of PWPs covered by selected studies

Country	Country acronym	PWP name	PWP acronym	Main implementation context	PWP classification
Côte d'Ivoire	CIV	Emergency Youth Employment and Skills Development Project - Labour Intensive Public Works Sub-Component	PEJEDEC-THIMO	(Semi-)urban (post-conflict)	Type 1 (Plus)
Ethiopia	ETH	Productive Safety Net Programme	PSNP	Rural	Type 2
Ethiopia	ETH	Productive Safety Net Programme + Other Food Security Programme/Household Asset Building Programme	PSNP + OFSP/HABP	Rural	Type 2 Plus
Ethiopia	ETH	Productive Safety Net Programme – High Value Food Basket	PSNP – HVFB	Rural	Type 2
Ethiopia	ETH	Employment Generation Schemes	EGS	Rural	Type 1
Ethiopia	ETH	Food-For-Work	FFW	Rural	Type 1
Ghana	GHA	Ghana Social Opportunity Project - Labour Intensive Public Works Programme	GSOP-LIPW	Rural	Type 1
Malawi	MWI	Malawi Social Action Fund Public Works Programme - Phase 3	MASAF III	Rural	Type 1
Rwanda	RWA	Vision 2020 Umurenge Programme	VUP	Rural	Type 1
Sierra Leone	SLE	Youth Employment Social Support Project/Cash for Work	YESP/CfW	Rural and urban (post-conflict)	Type 1

All retained studies are listed in Table A.2.5 of Appendix 2.A: List of studies selected for review. Four studies are randomised control trials (RCTs). They were conducted in Côte d'Ivoire, Malawi, Rwanda and Sierra Leone. The others are quasi-experimental studies that mostly use matching approaches, often in combination with difference-in-difference estimations. All studies investigating the PSNP fall into this category. Some of the more recent evaluations of the PSNP used a dose-response model where weakly treated PSNP households were compared to intensively treated PSNP households. Given that the PSNP is the only Type 2 PWP in this review, there is, thus, no evidence from an RCT for this programme type.

2.5 Method used for synthesising the evidence

The information in the studies was gradually condensed to the level reported here. First, all outcome indicators reported in the selected studies were entered into one comprehensive database, including the direction, magnitude and level of significance of each effect. If several estimation methods were used in a study, the authors' preferred estimates were chosen. In cases with several equally preferred methods, all of them were reported. To consider the nuances of study findings, the results of heterogeneity analysis (e.g., concerning programme variants, gender, urban/rural, or age) were also entered. The indicators were clustered into outcome areas. Second, the database was split by outcome area into several smaller databases. In each of these, only the studies that reported indicators for this outcome area were kept. Third, in each outcome area, similar indicators were clustered and the evidence patterns were categorised using the criteria reported in Table 2.3.¹⁰ In doing so, each study component or programme variant was treated as a separate study. Fourth, the patterns for each study were categorised using the same criteria.

Table 2.3: Categories to summarise the patterns of the empirical findings

Evidence pattern category	Explanation when it applies
Consistently positive/negative	Requires consistently positive/negative effects of closely connected indicators, several robust estimation methods or consistent patterns in the heterogeneity analysis. At least two effects must be significant at the 5% level or below.
Positive/negative trend	If only one effect is reported, this one must be positive/negative and significant. If several effects are reported, the majority of the effects must be positive/negative and significant.
Inconclusive	This applies in scenarios that are not captured by any of the other categories, e.g.: <ul style="list-style-type: none"> • Scenario 1: Several closely connected effects are reported. Some of them are statistically significant and positive. Others are statistically significant and negative. • Scenario 2: There are several statistically significant effects that point in the same direction, but there are also many effects that are not statistically significant. • Scenario 3: Two closely connected effects are reported. One is statistically significant (either sign), the other is not.
Insignificant	Only one effect is reported and it is not statistically significant.
Mostly insignificant	Several closely connected effects are reported. While there is a statistically significant effect, most effects are not significant.
Consistently insignificant	There is more than one reported effect and all of them are insignificant.
Single study	The outcome category has only been investigated in one single study. Study components reported in the same publication do not count as separate studies in this case.

Notes: *Positive* in this respect does not denote the algebraic sign but the desirable direction (i.e., improvements). Only if there is no desirable direction, does it denote the algebraic sign, which is then explicitly noted. Likewise, *negative* denotes the undesirable direction (i.e., deteriorations), if applicable.

¹⁰ In cases with several similar yet not identical indicators, an additional step was added in which the cells were assigned to the categories, but the clustering was not done immediately to its full extent in order to make sure that justice was done to the nuances of the findings in the fourth step.

I then conducted the analysis in Section 2.6 on the basis of the outcomes of these four steps and the contextual information from the reviewed studies. The typology proposed in Section 2.2 is used to differentiate variations in trends (or lack thereof) for the different PWP types. The paper reports only the outcome areas that were investigated in at least five studies (not counting study or programme variants as separate studies) and in at least two countries. These are income, consumption and expenditures, labour supply, food security, nutrition, asset holdings, agricultural production and techniques, and education.¹¹ Table 2.4 summarises which indicators were considered and synthesised for each outcome area.

Table 2.4: Indicators that were considered and synthesised in the review, by outcome area

Outcome area	Indicators
Income, consumption and expenditure	Total income, income from wage employment, income from self-employment, total consumption and expenditure, and non-food consumption and expenditure. ¹²
Labour supply	Number of economic activities, total hours worked, wage employment, self-employment (mainly referring to non-farm own business activities), non-farm activities, and the use of hired or shared labour.
Food consumption and food security	Food consumption, food expenditure, (crop-specific) food gap, the number of meals eaten, food security indices and scores, and expressed ‘worries’ about not having enough food.
Nutrition	Anthropometric outcomes and dietary diversity outcomes.
Asset holdings	Livestock indicators (e.g., number of livestock, value of livestock and tropical livestock units (TLUs)), durable consumption goods, productive assets and capital.
Agricultural production	Grain production output, grain acreage, and grain yield.
Agricultural technology	Expenditure on farm equipment and crop input, fertiliser use at intensive and extensive margin, dummy variables for pesticides use, improved seed use, irrigation use, stone terracing, fencing, and water harvesting.
Education	(Relative) grade attainment, enrolment, attendance, expenditure on education, expenditure on vocational training, and child cognitive abilities in math and languages (measured through test scores). Attendance and grade attainment are differentiated by gender.

To account for the treatment duration and intensity, I explicitly considered in the analysis whether the results refer to the short-term (≤ 1 year) or medium-term (> 1 year). In addition, the analysis reports whether the effects were measured after the end of programme participation. For many of the quasi-experimental studies, the treatment duration and intensity can only be approximated.

¹¹ The analysis of additional outcome areas (other support/transfers, loans, savings, child labour, health, resilience, and self-perceived wellbeing) are available on request. Some journal articles (Berhane et al., 2014; Hoddinott et al., 2012) were published on the basis of a more comprehensive evaluation report by Berhane et al. (2011). In such cases, only the results in the journal article were considered for each outcome area and programme variant. Results in the evaluation reports were only considered for outcome areas and programme variants that were not reported in the journal article. Likewise, if there were several versions of a study, none of which was a peer-reviewed journal article, the results in the most recent version were considered.

¹² The employment categories comprise indicators denoted in hours worked as well as dummy variables to indicate whether a household is engaged in such activities or not.

2.6 Review of programme effectiveness

2.6.1 Income, consumption and expenditure

Five of the 19 studies that report impacts on income, (non-food) consumption and expenditure find positive trends overall, but most studies detect no or only few significant effects. There is no clear positive pattern for any of the indicators. All PWP types are represented among the many studies without statistically significant effects, including cases where the sample was restricted to households that received a relatively high transfer value (Beegle et al., 2017; Gilligan et al., 2009b). Three of the five studies with positive findings concern Type 1 PWPs (from Côte d'Ivoire, Ethiopia and Sierra Leone). All three measured impacts while participants were still benefiting from the programme; two over the short-term (Bertrand et al., 2017; Rosas & Sabarwal, 2016) and one over the medium-term (Gilligan & Hoddinott, 2007). Only two of eight study variants that relate to the PSNP (i.e., Type 2) find positive trends overall. These two are the only ones where payments were not made exclusively in cash, but instead in mixed form or food only (Sabates-Wheeler & Devereux, 2010). Notably, there is to date no study that provides robust empirical evidence that a cash-based Type 2 (Plus) programme can sustainably boost total income or (non-food) consumption of participants' households in Sub-Saharan Africa beyond programme participation. With respect to the source of income, only the study of the Type 1 (Plus) PWP in Côte d'Ivoire tells a coherent story. Income from self-employment decreased while the programme was running, but afterwards it increased for participants that had received self-employment training and for participants that had received no extra training, but not for participants that had received wage employment training. The increase in self-employment income appears to have been driven by an increase in the profitability of existing activities (see Section 2.6.2), i.e., growth at the intensive but not extensive margin. Given that this PWP was implemented in a (semi-)urban context, it has limited external validity in rural contexts.

2.6.2 Labour supply

Although there are no strong indications that offering PW replaces other economic activities carried out by participating households (crowding out), there is also no indication that it boosts employment beyond the PW employment. This is consistent with the findings regarding income, consumption, and expenditure. Of the 23 studies that investigated labour supply, only the short-term evaluation of a Type 1 PWP in Sierra Leone finds a consistent increase in wage

and self-employment and a corresponding increase in income (Rosas & Sabarwal, 2016). Compared to other PWP, this programme targeted a particularly productive segment of the population (individuals aged 15-35 in poor communities). This may explain its exceptional result. One evaluation of Ethiopia's PSNP also finds a statistically significant increase in self-employment (Gilligan et al., 2009b), but the other PSNP evaluations do not substantiate this finding (Berhane et al., 2011; Gilligan et al., 2009a). As noted, offering complementary self-employment training through the Type 1 Plus PWP in Côte d'Ivoire did not increase employment in the short to medium-term but it did boost productivity (Bertrand et al., 2016, 2017). The two studies that investigated the use of hired or shared labour by participating households (Ethiopia and Malawi) as proxies for general labour market effects, find no effects (Beegle et al., 2017; Gilligan et al., 2009a).

2.6.3 Food consumption and food security

Of the 22 studies that investigated food consumption and food security, 17 cover Ethiopia of which all but one are from the PSNP and its variants. The overall picture from the PSNP is positive, whereas it is inconclusive for Type 1 PWPs. All evaluations of Ethiopia's Type 2 Plus variant find overall positive impacts although there has been no investigation into whether this persists beyond the time on the programme (Berhane, 2014; Gilligan et al., 2009b, 2009a). By contrast, there are no strong indications that the OFSP on its own improved food security (Gilligan et al., 2009a). The overall findings regarding the Type 2 variant (PSNP only) are somewhat mixed due the inconclusive picture for food consumption, but positive for food security. The food gap is consistently found to narrow. The evidence for Type 1 PWPs is inconclusive. Unlike the studies from Ghana, Rwanda and Sierra Leone, the study from Malawi does not find any indications of improvements even though it reports many indicators and one study variant where participants received twice the transfer value. This suggests that Type 1 programmes can stabilise food consumption in the short term, but that this cannot be taken for granted.

2.6.4 Nutrition

Eleven of the twelve studies where impacts on nutrition were investigated relate to Ethiopia and most of those to the PSNP and its variants. While these studies mostly focus on anthropometric outcomes, the evaluation of a Type 1 PWP in Malawi investigated only dietary diversity outcomes. Regarding dietary diversity, there are no indications of improvements when payment was predominantly in cash. However, one study relating to Ethiopia detects improvement

driven by the programme variant where payment was in food (Debela et al., 2017). Regarding anthropometric outcomes, the findings from Ethiopia are inconclusive for both acute and chronic undernutrition. Two evaluations of the PSNP (Type 2) find reductions in acute and chronic undernutrition, whereas three evaluations do not, even when the sample is restricted to households that received a higher transfer value (Gilligan et al., 2009a). An evaluation of an Ethiopian Type 1 PWP finds no strong indications of improvements (Quisumbing, 2003).

2.6.5 Household asset holdings

21 of the 30 studies that measured impacts on asset holdings concern Ethiopia. Of them, all but one focus on the PSNP. The overall picture across the diverse outcome areas and programme variants is inconclusive. However, a differentiation by PWP type and variant provides some interesting insights. No clear picture emerges for Type 1 PWPs. Evaluations of such programmes in Rwanda and in Sierra Leone find an increase in livestock ownership in the short-term. They also find an increase in other assets, in contrast to the evaluation of Malawi's Type 1 PWP, which does not. The evaluation of the Type 1 (Plus) programme implemented in a (semi-)urban context in Côte d'Ivoire finds growth in the asset base in the short-term (Bertrand et al., 2017). This is also the case in the medium-term for the standalone Type 1 variant of the programme, but not for the Type 1 Plus variants. The evaluation of a Type 1 PWP in Ethiopia even detects a decrease in the value of livestock, though this appears to be driven by positive outliers in the control group (Gilligan & Hoddinott, 2007).

While the overall results regarding the PSNP alone (Type 2) are also inconclusive, most studies find increases in livestock ownership. The findings for the other asset categories are mostly insignificant and, in rare cases, even negative. The results by Sabates-Wheeler and Devereux (2010) suggest that the Type 2 variant in which wages were paid in food performs better than the variants with mixed payment and cash only. However, this difference may be mainly driven by the higher imputed value of the food compared to the cash.

Although the evidence is not consistently positive, the Type 2 Plus variant in Ethiopia seems to outperform the other variants with respect to asset accumulation, especially livestock. The trends for livestock ownership are positive in three of the four Type 2 Plus evaluations. One of the two studies that looked at productive assets also finds positive trends (Berhane et al., 2011). However, the difference for Type 2 Plus compared to the Type 2 variant alone or compared to the Plus components alone is not statistically significant. Moreover, there is no robust evidence to date whether asset accumulation persists beyond the end of the programme.

2.6.6 Agriculture

20 of the 27 studies that investigated impacts on agricultural outcomes relate to Ethiopia. Of these, all but one focuses on the PSNP. Five of them are standalone Plus components. The agricultural outcomes are grouped into two main categories: agricultural technology and agricultural production. The overall picture is inconclusive but differentiating by PWP type and variant for each of these two categories yields some patterns.

Regarding agricultural technology adoption, the Type 2 Plus variant of the PSNP performs well overall and outperforms the Type 2 variant. In particular, fertiliser use and the adoption of stone terracing and fencing are found to increase. The same applies to improved seed use, but this was investigated in just one study (Gilligan et al., 2009b). The results are less unequivocally positive for more specific Type 2 Plus variants (Gilligan et al., 2009a). The positive effects of the usage of agricultural technology do not in all cases translate into tangible increases in agricultural production. In fact, the regular Type 2 Plus variant of the PSNP neither outperforms the Type 2 variant (PSNP alone) nor the main control group in agricultural production.¹³ It merely leads to an increased grain yield compared to the Plus component alone, but no difference for output or acreage is found.

There are no indications that the Type 2 variant has noteworthy effects on agricultural technology adoption or agricultural production. With respect to technology adoption, most results are not statistically significant. One study detects an increased use of fencing, an outcome that was not investigated in any other study (Hoddinott et al., 2012). With respect to agricultural production, the only positive trend is detected for grain acreage in the HVFB area, but this has not led to higher production (Gilligan et al., 2009a).

Agricultural technology adoption and production are rarely investigated in the context of Type 1 programmes. The evidence regarding agricultural technology adoption is inconclusive. The study focusing on Côte d'Ivoire finds an increase in agricultural expenditure in the short term. However, it does not persist in the medium-term for any of the programme variants. No impact is found in Rwanda. Fertiliser use in Malawian programme study has not increased although the programme aimed at creating complementarities with the country's large fertiliser subsidy scheme. By contrast, an increase in the share of households using fertiliser is detected for a Type 1 PWP in Ethiopia, but those that used fertiliser did not increase the quantity applied. The

¹³ The main control group consisted of PSNP participants that were in the programme for no more than a year.

Rwandan study finds neither an increase in expenditure on crop inputs nor in agricultural production output.

2.6.7 Education

Of the 19 studies that look at education, 11 relate to Ethiopia. 10 of these focus on the PSNP. The available evidence is limited to the short to medium-term. The increase in labour supply by participants' households could come at the expense of the time children spend in school because the children are required to engage more in household chores or farm work. However, none of the studies suggests that this happens. However, there are also no indications of wide-spread improvements in education outcomes through any of the programme types with the partial exception of the Type 2 variant of the PSNP. The eight studies into Type 1 PWPs covering Côte d'Ivoire, Ethiopia, Rwanda and Sierra Leone do not find any evidence for positive (or negative) effects on education.

Regarding Type 2 programmes, the findings suggest that a higher transfer value leads to better education outcomes, although it appears to affect boys and girls differently. The only study that looks at grade attainment from this angle finds deteriorations for both sexes, but especially girls, when the transfer value is low. By contrast, a higher transfer value leads to improvements for girls but not boys (Berhane et al., 2016). The studies that do not differentiate for differences in the transfer value find no effects (Tafere & Woldehanna, 2012; Woldehanna, 2009). The only study that investigates enrolment for Type 2 finds no impact, irrespective of the transfer value (Berhane et al., 2016). Equally, there are no strong indications of changes in school attendance, although one of the two studies that differentiate by transfer value finds increased attendance for boys when transfer values are higher (Hoddinott et al., 2009, 2010). With respect to cognitive abilities, some positive effects are documented in Berhane et al. (2015) and Favara et al. (2019).¹⁴ Only one study looks at the education outcomes of the Type 2 Plus variant of the PSNP. It finds no impact on attendance (Hoddinott et al., 2009, 2010).

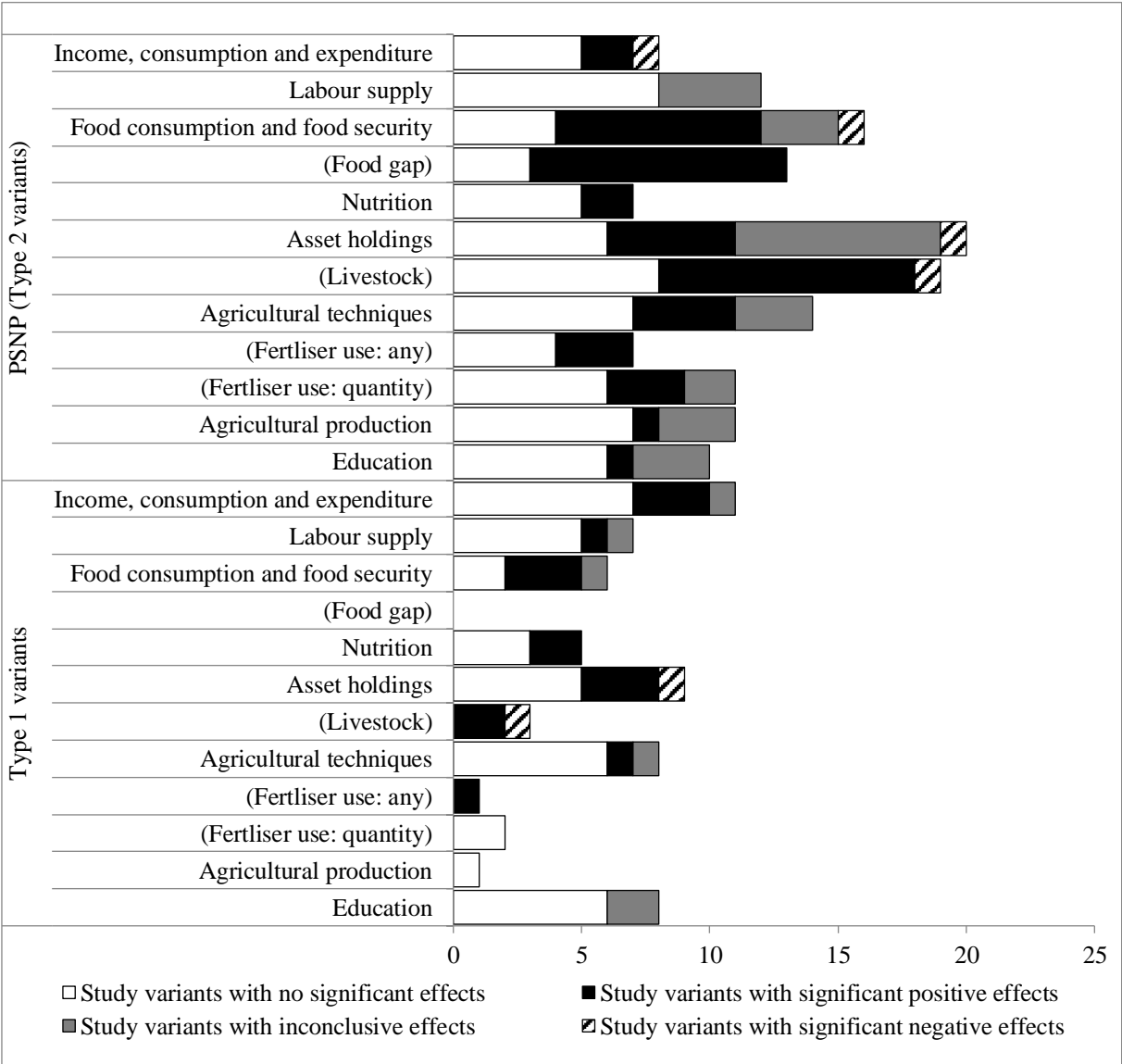
2.6.8 Pulling it all together

After having synthesised the results separately for each outcome area, the general evidence can now be summarised. Study variants concerning Ethiopia account for more than half of the observations in all outcome areas. Figure 2.2 visualises the differentiation of the overall results

¹⁴ Another study found that the PSNP in Ethiopia increases children's educational aspirations (Gebremariam, Lodigiani, & Pasini, 2017).

by PWP type. Additionally, the Appendix contains a summary figure (Appendix 2.B: Figures for each outcome area) and summary table (Appendix 2.C: Tables for each outcome area) for each outcome area. Note that differences in reported indicators or the low number of observations often limit the viability of directly comparing the performance between Type 1 and Type 2.

Figure 2.2: Evidence patterns for all outcome areas at a glance



Regarding Type 1 programmes, the share of studies that detect positive trends for the respective outcome area is low for all outcome areas except food consumption. In all other outcome areas, the majority of studies detect mostly insignificant effects. However, it seems that Type 1 programmes can achieve modest objectives such as consumption smoothing, even if not all programmes do so. The evidence relating to Type 2, represented by Ethiopia’s PSNP, is overall

insufficient to safely infer that it outperforms the Type 1 programmes such that the difference is commensurate with its larger ambitions and higher costs. The standalone variant of the PSNP (Type 2) is found effective in improving food security in the medium-term. Moreover, it seems to positively affect some educational outcomes unless the transfer share is particularly low. However, there is no strong support that Type 2 outperforms Type 1 programmes in facilitating asset accumulation or agricultural outcomes and, thus, in putting households on an upward trajectory. The Type 2 Plus variant of the PSNP performs better than the other PWP types in some respects. It does well in asset accumulation, especially livestock, and agricultural technology adoption. However, there are no strong indications of an increase in income or agricultural output in the medium-term. Moreover, there is to date no study that provides robust empirical evidence that a Type 2 Plus programme can sustainably strengthen the livelihoods of participants' households well beyond their time on the programme.

2.7 Discussion of the drivers of programme effectiveness

The mixed findings regarding programme effectiveness might suggest that PWPs are not *per se* ineffective, but rather that they can be effective under certain conditions, including the specific design and implementation features. This section, therefore, highlights what is known about the drivers of programme effectiveness. I draw on the limited evidence from the studies reviewed in the previous section and complement it with observational and qualitative evidence, including a few studies that relate to countries outside Sub-Saharan Africa, and make some theoretical considerations. The focus is on key design features where the expected link to programme effectiveness is strong. The implementation of PWPs is prone to many potential pipeline breaks because they are so administratively demanding. While some of the studies considered in the review contain information as to whether and where implementation fell short, it remains mostly unclear how (much) this affected impacts.

2.7.1 PW payments

In short, the literature recommends that the total transfer value is commensurate with the programme objectives, the nature, extent and depth of poverty and vulnerability, and the labour market context in the country (McCord, 2012). This includes giving consideration to the various types of monetary and non-monetary opportunity costs that participating in a PWP may entail. The impacts realised through wage transfer are expected to depend on the real value of the

transfer for the household in relation to the household poverty gap. In fact, many studies cite low wage rates as the key factor in explaining limited impacts (Bloom et al., 2005; Chirwa et al., 2004a, 2004b; Gilligan et al., 2009b; P. White & McCord, 2006; World Bank, 2015). While few studies robustly test whether higher transfer values indeed result in higher impacts, there are some that exploit non-randomised variation in transfer amounts (Beegle et al., 2017; Debela et al., 2017; Gilligan et al., 2009a, 2009b). Debela et al. (2017) find that among PSNP participants who received their payment in food, those with longer exposure to the programme consumed a more diversified diet. Yet, overall the studies find few noteworthy differences. This may be because in these cases even the higher transfer values were still relatively low from a social protection perspective.¹⁵ Generally, there is a lack of evidence from Sub-Saharan Africa to ascertain whether a PW wage rate above the market rate crowds out workers from the private sector.¹⁶ If such concerns seem warranted, or if increasing the wage rate is not politically feasible, extending the number of workdays offered may be an alternative. If there is a risk of oversubscription due to the relative attractiveness of the transfer value, a targeting mechanism that prevents substantial targeting errors is needed.

If payments are not made regularly as planned, or if payments are not the expected amounts, the ensuing lack of predictability weakens the insurance function and, thus, undermines the benefits that might come from it (Gehrke, 2017). Studies covering Ethiopia's PSNP point out that implementation shortcomings during the first five years of the programme's operation, especially irregular payments, may have lowered impacts (Berhane et al., 2016). Judged on the basis of one single RCT relating to rural Malawi, there are no indications that varying the frequency of payments (several smaller instalments vs. fewer larger instalments) leads to differential impacts (Beegle et al., 2017). In fact, in this case none of the two payment modalities had any effect on food security.

There are good reasons to use cash as the standard payment modality, but there are situations, especially in times of acute food shortages, when payment in food may be preferable (Maunder & Wiggins, 2006; Sabates-Wheeler & Devereux, 2010; Save The Children, 2008; Slater et al., 2006). For example, Sabates-Wheeler and Devereux (2010), who quantitatively differentiated

¹⁵ In Malawi, it corresponds to 14% of the country's gross national income per capita (Beegle et al., 2017). In Ethiopia, the higher transfer value group comprised many households that received considerably less than was foreseen by the programme at that time, namely a daily wage rate equivalent to the value of half a daily grain portion (Gilligan et al., 2009b).

¹⁶ Small effects of this kind were detected for the Labour-Intensive Public Works Programme (LIWP) in Yemen (Christian et al., 2015) and substantial effects, as noted earlier, for the Indian MGNREGA programme (Imbert & Papp, 2015; Muralidharan et al., 2018; Zimmermann, 2014).

the impacts of three different payment modalities in the context of the early years of Ethiopia's PSNP, find that the variants where wages were paid in food only or as a mix of food and cash, performed better overall than the cash only variant because the value of the latter was eroded by price inflation.

2.7.2 Timing of PW

Three sets of questions need to be addressed when PW activities and payments are planned: When and how much excess labour capacity do PW participants have? When are they most in need of receiving income support and what are they likely to use it for? When are certain types of PW activities best undertaken so that the created assets unfold to their full potential? The answers may not necessarily align and, hence, policy makers must be aware of possible trade-offs. Decoupling the timing of work and payments may help to avoid some trade-offs. Timing may influence the use of payments because spending priorities vary seasonally (Chirwa, 2012). However, the results from an RCT in Malawi demonstrate that varying the timing does not necessarily have the intended effects. Food security did not improve, irrespective of whether the PWP activities, and, hence, payment, took place during the lean or the harvest season (Beegle et al., 2017). Fertiliser use also did not increase, even though the timing of activities was specifically chosen to enable participants to access subsidised farm inputs.

In principle, scheduling the bulk of the PW activities during periods when other employment opportunities are rare (i.e., outside the planting and harvest seasons) is recommended as one way to reduce the opportunity costs of participating in a PWP (Holden et al., 2006). However, the literature suggests that there may still be room for some time-critical PW activities at times of peak labour demand because there is some – albeit small and varying – excess supply of labour at these times in Sub-Saharan Africa (Beegle et al., 2017; Debela et al., 2017; Dillon et al., 2017). To get it right requires a good understanding of rural labour markets, especially in terms of spare labour availability and how it varies throughout the year, in different areas and for different household types.

2.7.3 Asset creation through PW

The available impact evaluations are largely silent on the role of the asset vector. In fact, none of the studies reviewed in Section 2.6 isolate the role of the wage vector from the role of the

asset vector.¹⁷ However, two other studies quantified the effects that the work activities of Ethiopia's PSNP have on agricultural outcomes. Gazeaud and Stéphane (2020) do not find evidence that agricultural productivity improved in programme areas where soil and water conservation activities took place. Filipski et al. (2017) find an average yearly increase in grain yields of 2.8% but no effect for non-grain crops. Furthermore, they detect a 12% growth in vegetable yields per irrigation project. These mixed findings imply that it must not be taken for granted that the assumed productive effects of PW assets materialise.

The wider literature suggests that the following factors jointly determine the quality, sustainability and relevance of the assets created: First, quality materials must be used, whereby local procurement is commendable but not if it means compromising on quality, as was observed in some studies (e.g., D R Consulting, 2013). Second, to provide a broad safety net, high labour intensity in the PW projects is desirable but, again, not if it comes at the expense of asset quality (Chirwa, 2012; Gehrke & Hartwig, 2015; Lieuw-Kie-Song, 2014; McCord, 2012; Train4Dev, 2009; P. White & McCord, 2006; World Bank, 2015). Too rigid caps on the share of non-labour costs are found to be detrimental. To avoid this, the literature recommends aligning the caps with the capital requirements of the chosen PWP activity and to allow for some leeway to accommodate changing needs (McCord & Slater, 2009; Subbarao et al., 2013). Third, adequate technical expertise, facilitation support, management capacity, construction oversight, and minimum standards set out in technical manuals and management guidelines are needed (Holden et al., 2006; Lieuw-Kie-Song et al., 2010; World Bank, 2015).

Fourth, whether and how community participation matters for delivering lasting impacts through the asset vector is not clear as it depends on the context as well as the kind and intensity of participation (Mansuri & Rao, 2013). Participation may arguably strengthen local ownership which is often assumed to enhance the sustainability of assets and to minimise the risk of crowding out private investment (Costella & Manjolo, 2010; World Bank, 2010). Holden et al. (2006) support this assertion empirically for soil and water conservation projects of a Type 1 PWP in Northern Ethiopia. However, other empirical studies question the general validity of this assumption. A quasi-experimental study finds that the quality of the soil and water conservation structures built through the PSNP in Ethiopia improved in cases where communities played an important role in monitoring and evaluation. However, community

¹⁷ Evidence on the matter is similarly scarce for other regions although Gehrke (2015) investigated the employment effects of the PW infrastructure created through India's MGNREGA.

participation in planning and implementation, as well as in usage and maintenance, did not make a statistically significant difference (Shigute, 2019). For Pakistan, Khwaja (2004) finds that community participation in technically demanding decisions and steps may negatively affect asset quality if the communities lack the necessary technical expertise. Moreover, community participation comes with a risk of elite capture (Mansuri & Rao, 2013) and, if done properly, is more time consuming (Devereux & Macauslan, 2006; McCord & Farrington, 2008). Fifth, the literature recommends effective (and, if necessary, adequately financed) maintenance arrangements with clearly assigned responsibilities as an integral part of project planning from the get-go (Chirwa, 2012; Chirwa et al., 2004a; Lieuw-Kie-Song, 2014; Subbarao et al., 2013). The strategy to include those people in maintenance groups who are expected to benefit the most from the assets, allows for capitalising on their inherent interest in maintaining the asset (Lieuw-Kie-Song, 2014). Sixth, PW activities that are consistent with the national development plan but also embedded in a multi-year local development plan ensure coherence with other local development initiatives and strategic consistency (McCord, 2012; von Braun, 1991).

2.7.4 Skills development through PW

As for the asset vector, robust evidence on the role of the skills vector in PW is rare. Only two studies in our review explicitly look at it (Andersson et al., 2011; Bertrand et al., 2017). Gehrke and Hartwig (2018) provide an overview of the literature, including these two studies. In what follows, their main policy conclusions are revisited and adapted to the more specific context of Sub-Saharan Africa. Unemployment in Sub-Saharan Africa, even more than elsewhere, is not primarily due to a skills gap (i.e., a mismatch between demanded skills and the skill sets of the unemployed), but rather the outcome of low labour demand. This limits the potential of PWPs to serve as a bridge to market-based employment through skills development (Lieuw-Kie-Song, 2014; McCord, 2012). In such cases, the literature recommends focusing on skills that are useful to increasing income from micro-entrepreneurial activities or agricultural production (McCord, 2012).

There is some evidence that on-the-job training can be a cost-effective way to convey knowledge and skills, especially if they are applicable to the household farming activities of PW participants or other relevant income-generating activities. For example, one study finds that on-the-job training in forestry and soil and water conservation as part of the Ethiopian PSNP created skills that participants applied later in their own community and on their own farms (Andersson et al., 2011).

The empirical case for formal training components in PWPs is weaker than the case for on-the-job training. Studies find that, irrespective of their link to PWPs, skills development courses tend to be costly and rarely enhance future employment prospects to the expected extent (Betcherman et al., 2004; Blattman & Ralston, 2015; Kabeer, 2009; McKenzie, 2017). The RCT evaluation of the Type 1 Plus PWP in Côte d'Ivoire assesses the effects of two separate formal training components (Bertrand et al., 2017). The treatment arm offering complementary wage employment training, does not outperform the regular Type 1 programme. However, some positive effects associated with the treatment arm offering self-employment training were detected one year after the programme ended. Given that in contrast to most other PWPs in the region, this Type 1 Plus programme was implemented in a (semi-) urban context, its external validity is certainly limited. Gehrke and Hartwig (2018) state that in order to be effective, the training must address knowledge gaps, schedule sufficient contact time, and be geared towards enabling participants to capitalise on actually existing and viable economic opportunities. Implementation capacity is often severely limited in Sub-Saharan Africa. Thus, adding extra components to a PWP may come at the expense of the core PW component. In short, the evidence does not call for an outright dismissal of adding formal training components to PWPs. Instead, it emphasises the need to have a convincing rationale why the combination is likely to have added value and be cost-effective relative to alternative uses of the funds spent on skill development.

2.8 Conclusion

This paper reviews what is known about the impacts of public works programmes (PWPs) in Sub-Saharan Africa in a way that accounts for the heterogeneity in programme design and implementation context. The paper uses a typology of PWPs to structure the analysis. It looks at the effects of PWPs on several outcome areas: income, consumption and expenditure, labour supply, food consumption and food security, nutrition, asset holdings, agricultural technology adoption and production, and education. Overall, the findings regarding each outcome area are mixed but some of the reviewed studies convincingly explain why and for whom certain impacts materialise in a given case or not. For example, the evaluation of a Type 1 Plus programme in Côte d'Ivoire finds an increase in the productivity of non-agricultural self-employment one year after the end of the programme. This effect is primarily driven by the participants that participated in complementary self-employment training and not by those who

underwent wage employment training (Bertrand et al., 2017). Another example is an evaluation of Ethiopia's Productive Safety Net Programme (PSNP), the only Type 2 programme in the review. Its results suggest that a low transfer value decreases educational grade attainment for both sexes, while a higher transfer value leads to improvements for girls but not for boys (Berhane et al., 2016). Due to such examples, the overall mixed findings are not considered as evidence that PWP are *per se* ineffective, but rather that they can be effective under certain conditions, including the specific design and implementation features. Therefore, the paper also reviews what is known regarding the role of key programme features.

In particular, the review offers insights into the question which PWP model is appropriate in which context and how the programmes perform compared to each other. In alignment with the findings in earlier cross-country studies (Gehrke & Hartwig, 2018; McCord, 2012), Type 1 programmes seem only to be suitable in contexts of acute poverty and to achieve basic objectives, such as enabling short-term consumption smoothing. However, even this is not guaranteed, especially if the transfer share (i.e., wages in relation to the household poverty gap) is low. The evidence relating to Type 2, represented by Ethiopia's PSNP, is overall too inconclusive to safely infer that it clearly outperforms the Type 1 programmes which are still more common in the region. With reference to the period of PWP participation, the PSNP without its complements appears to improve food security and some educational outcomes unless the wage transfer share is particularly low. However, there is no clear evidence that Type 2 outperforms Type 1 in facilitating asset accumulation or agricultural outcomes and, thus, in putting households on an upward trajectory. The PSNP with its complements, the Other Food Security Programme and its successor, the Household Asset Building Programme, (Type 2 Plus) performs better than the other PWP types in asset accumulation (especially of livestock) and agricultural technology adoption. However, there are no strong indications that income or agricultural output of PWP participants increase in the medium-term. Moreover, there are to date no studies that investigate whether a Type 2 Plus programme can sustainably strengthen the livelihoods of participants' households well beyond their time on the programme. Evidence is also mixed regarding agricultural outcomes in localities where PSNP aimed to boost productivity through soil and water conservation activities (Filipski et al., 2017; Gazeaud & Stéphane, 2020). The reliance on the PSNP as the only Type 2 (Plus) programme in the region, the lack of evidence for long-term effects, for impacts through the asset and skills vectors, for the role of contextual factors, as well as for the added value of specific design factors prevents

drawing strong policy conclusions about the full potential of PWPs in general, and different PWP types in particular. Moreover, it may be that the statistical power in some of the reviewed studies was insufficient to capture small effects in investigated outcome areas.

Taken together, the review also corroborates the finding of Gehrke and Hartwig (2018) that the existing evidence is too patchy and mixed to claim that PWPs generate effects that go beyond those of cheaper alternative interventions like cash transfer programmes. The evidence base for the impacts of cash transfer programmes is broad and firmly established, as epitomised in the review by Bastagli et al. (2016, 2019). Regarding education and nutrition, the evidence suggests that regular cash transfer programmes perform better in these outcome areas than in any of the PWP types. For the other outcome areas, it is less clear. For the time being, therefore, the case for PWPs vis-à-vis regular cash transfer programmes continues to rest mainly on assumed benefits. More research and thorough evaluations are needed to find out under what design and implementation features PWPs can unfold their full potential and whether the cost-benefit comparison with cash transfer programmes comes out favourably.

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Appendix

Appendix 2.A: List of studies selected for review

See Table A.2.5.

Table A.2.5: List of studies selected after applying the inclusion criteria and the search strategy

Author(s)	Publication Type	Country	Programme acronym	Evaluation duration in years	Study type	Identification strategy
Andersson et al. (Andersson et al., 2011)	Journal article	ETH	PSNP	2	Quasi-exp.	PSM, regression analysis
Beegle et al. (2017)	Journal article	MWI	MASAF III	3	RCT	DID (ITT)
Béné et al. (2012)	Working paper	ETH	PSNP	2	Quasi-exp.	PSM
Berhane et al. (2011)	Evaluation report	ETH	PSNP	4 (dose-response)	Quasi-exp.	Matching & DID on a dose-response model
Berhane et al. (2014)	Journal article	ETH	PSNP	4 (dose-response)	Quasi-exp.	Matching & DID on a dose-response model
Berhane et al. (2015)	Working paper	ETH	PSNP	3	Quasi-exp.	Matching & DID
Berhane et al. (2016)	Evaluation report	ETH	PSNP	2, 4 and 6	Quasi-exp.	Inverse probability weighting regression adjustment estimators
Bertrand et al. (2016)	Evaluation report	CIV	PEJEDEC-THIMO	Short-term 0.4 Medium-term: 2	RCT	ITT using OLS regression (probability weights)
Bertrand et al. (2017)	Unpublished paper	CIV	PEJEDEC-THIMO	Short-term 0.4 Medium-term: 2	RCT	ITT using OLS regression (probability weights)
Bezu & Holden (2008)	Journal article	ETH	FFW	Cross-sectional data	Quasi-exp.	Heckman selection model
Debela et al. (2015)	Journal article	ETH	PSNP	Cross-sectional data	Quasi-exp.	Exogenous switching regression
Debela et al. (2017)	Working paper	ETH	FFW; PSNP	Dose-response	Quasi-exp.	Binary TV: FE, RE, DID; continuous TV: control function approach (1 st stage RE Tobit model, 2 nd stage RE model), dose-response model
Favara et al. (2019)	Journal article	ETH	PSNP	Medium-term	Quasi-exp.	OLS estimate of a conditional demand function for child cognitive ability
Gebrehiwot & Castilla (2019)	Journal article	ETH	PSNP	Up to 2 (dose-response model)	Quasi-exp.	2SLS, reduced form IV, generalised PSM (maximum likelihood) with continuous TV; DID, PSM
Gilligan & Hoddinott (2007)	Journal article	ETH	EGS	1.5	Quasi-exp.	PSM & DID
Gilligan et al. (2009a)	Journal article	ETH	PSNP	1.5	Quasi-exp.	PSM
Gilligan et al. (2009b)	Evaluation report	ETH	PSNP	2	Quasi-exp.	NNM
Hartwig (2013)	Unpublished paper	RWA	VUP	1.25	Quasi-exp.	NNM & DID
Hoddinott et al. (2009)	Unpublished paper	ETH	PSNP	Cross-section	Quasi-exp.	NNM
Hoddinott et al. (2012)	Journal article	ETH	PSNP	4 (dose-response)	Quasi-exp.	Dose-response model
Osei-Akoto et al. (2014)	Unpublished paper	GHA	GSOP-LIPW	1	Quasi-exp.	PSM
Porter & Goyal (2016)	Journal article	ETH	PSNP	3	Quasi-exp.	PSM; DID; sibling-differences
Quisumbing (2003)	Journal article	ETH	FFW		Quasi-exp.	Arellano-Bond GMM estimator
Rosas & Sabarwal (2014, 2016)	Working paper / unpublished paper	SLE	YESP/CfW	0.3	RCT	ITT using OLS regression; LATE
Sabates-Wheeler & Devereux (2010)	Journal article	ETH	PSNP	2	Quasi-exp.	Growth regression model using OLS multivariate regression analysis
Tafere & Woldehanna (2012)	Working Paper	ETH	PSNP	3	Quasi-exp.	Matching & DID
Weldegebriel & Prowse (2013)	Journal article	ETH	PSNP	Cross-section	Quasi-exp.	PSM (NNM, radius, kernel, direct NNM)
Woldehanna (2009)	Working paper	ETH	PSNP; EGS	PSNP: 1 year FFW: up to 3 years	Quasi-exp.	PSM

Notes: ITT denotes ‘intent-to-treat’, OLS denotes ‘ordinary least squares’, PSM denotes ‘propensity score matching’, DID denotes ‘difference-in-difference’, TV denotes ‘treatment variable’, FE denotes ‘fixed effects’, RE denotes ‘random effects’, 2SLS denotes ‘two-stage least squares’, IV denotes ‘instrumental variable’, NNM denotes ‘nearest neighbour matching’, and LATE denotes ‘local average treatment effect’.

Appendix 2.B: Figures for each outcome area

Figure B.2.2.3: Income, consumption and expenditure

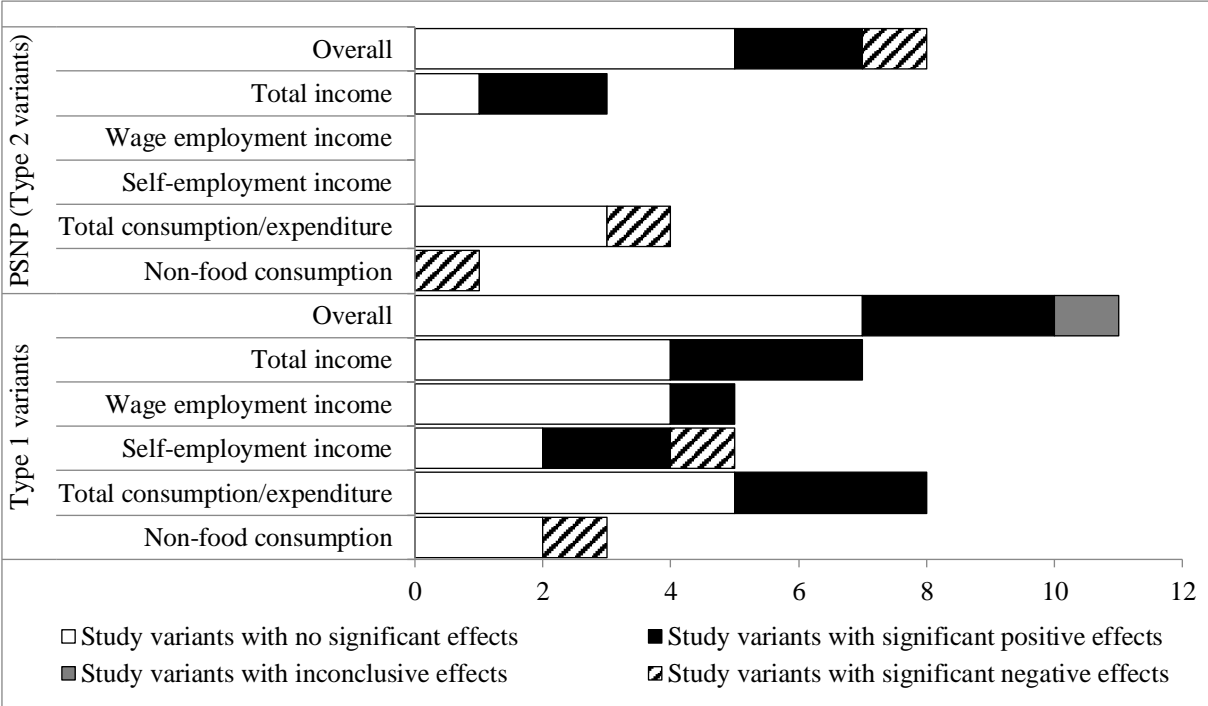


Figure B.2.2.4: Food consumption and food security

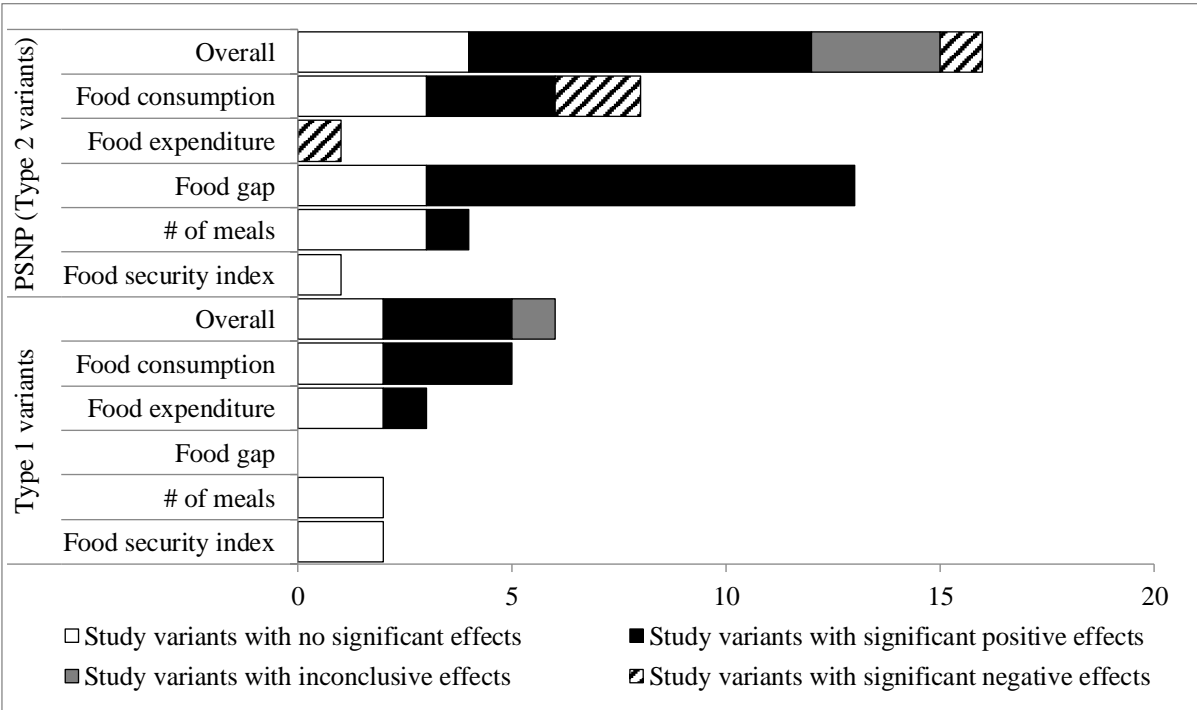


Figure B.2.2.5: Labour supply, without Plus programmes

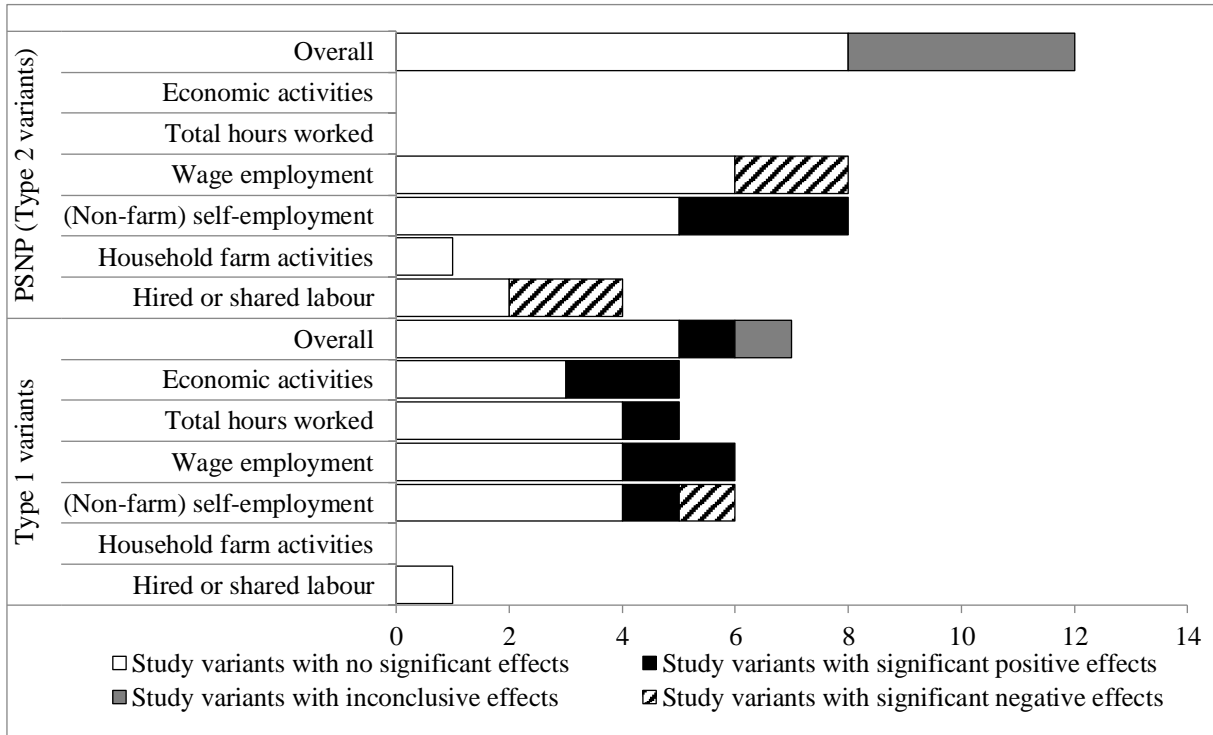


Figure B.2.6: Labour supply, with Plus programmes

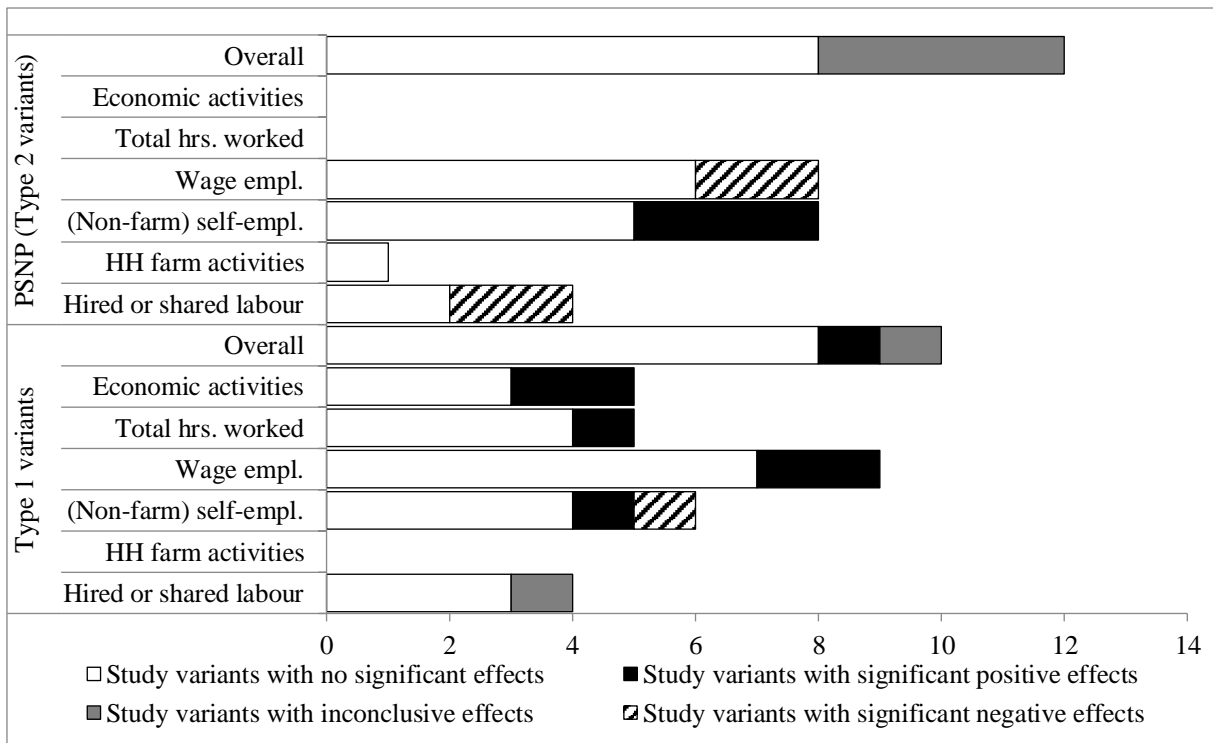
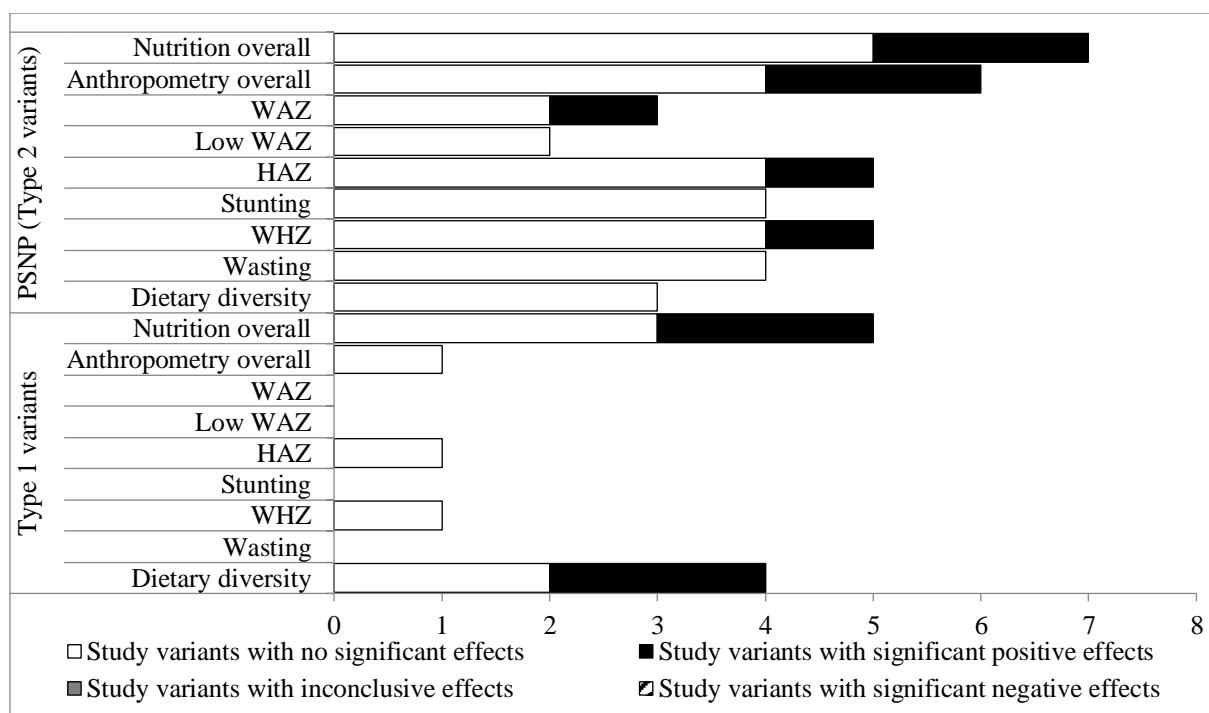


Figure B.2.2.7: Nutrition



Notes: 'WAZ' denotes 'weight-for-age z-score', 'HAZ' denotes 'height-for-age z-score' and 'WHZ' denotes 'weight-for-height z-score'. The study by Debele et al. (2017) is classified as Type 1 in this figure although they evaluate a mix of Type 1 and Type 2 (because the evaluation period covers the time when the then existing Type 1 programmes were substituted by the Type 2 programme PSNP).

Figure B.2.2.8: Household asset holdings

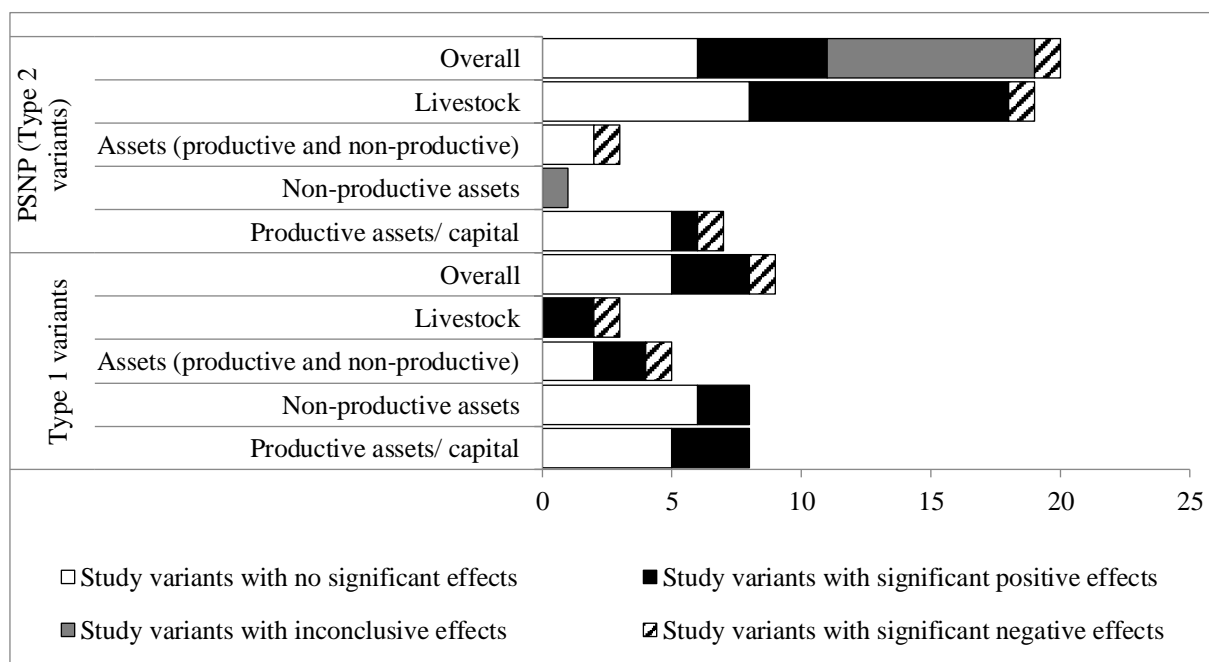


Figure B.2.2.9: Agricultural technology, without Plus Programmes

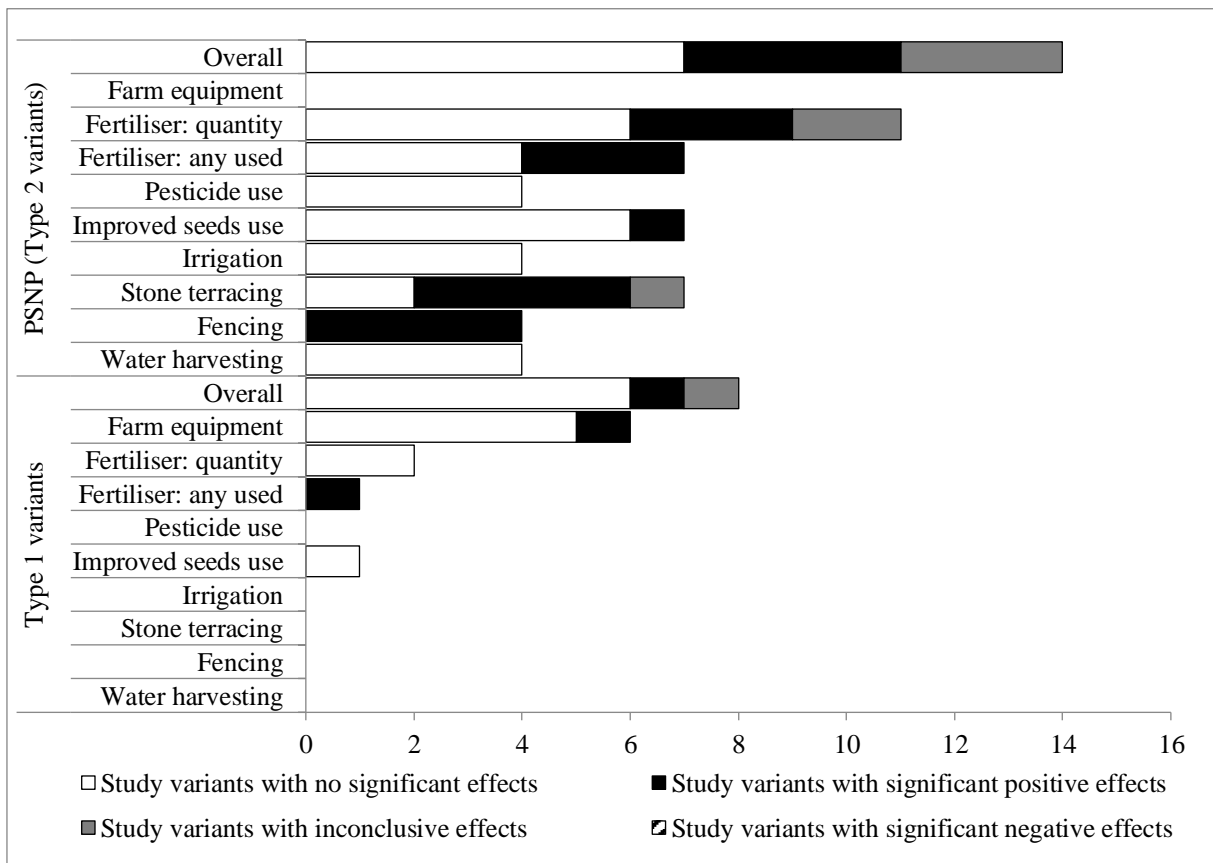


Figure B.2.2.10: Agricultural production and agriculture overall

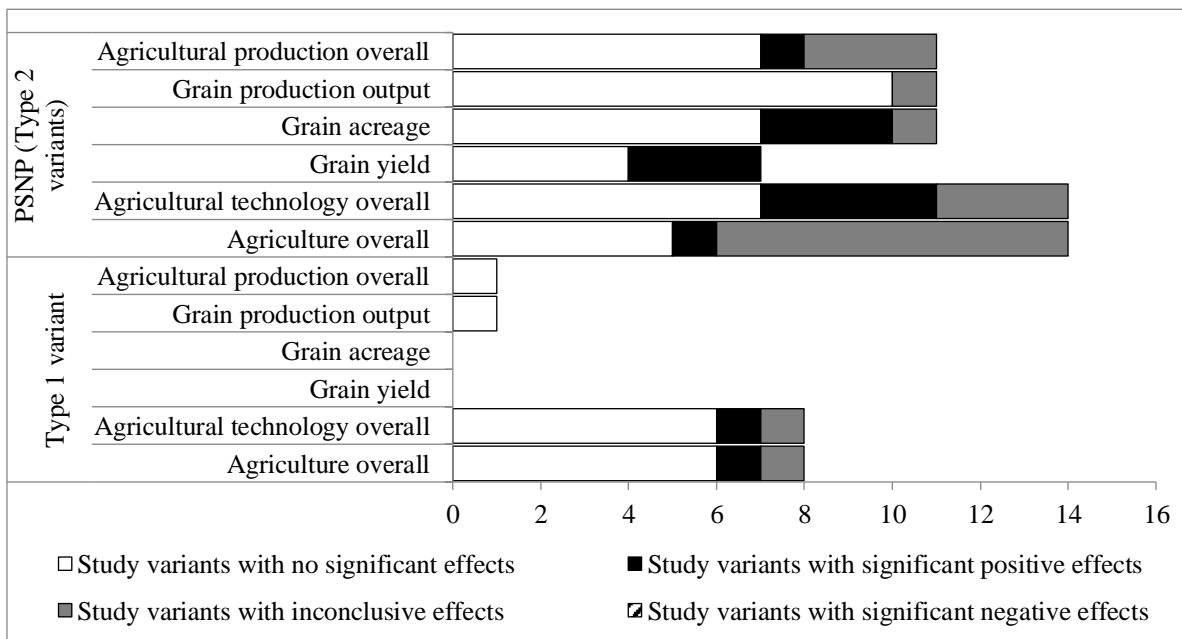
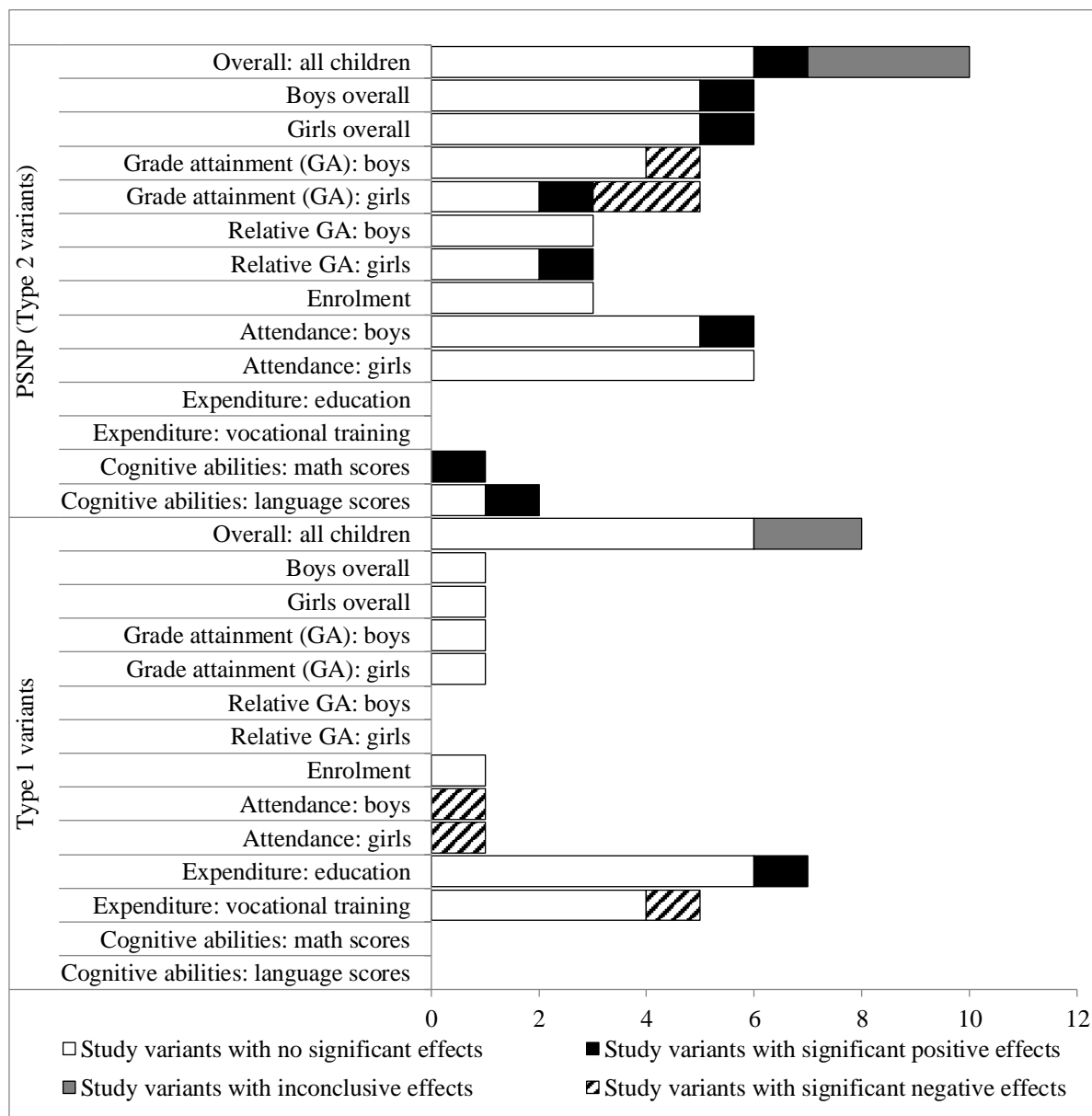


Figure B.2.2.11: Education



Appendix 2.C: Tables for each outcome area

Note: In Table C.2.6 to Table C.2.13, the following abbreviations are used: ‘Cst. +’ denotes ‘consistently positive’, ‘Cst. -’ denotes ‘consistently negative’, ‘Trend +’ denotes ‘positive trend’, ‘Trend -’ denotes ‘negative trend’, ‘Cst. ins.’ denotes ‘consistently insignificant’, ‘Mos. ins.’ denotes ‘mostly insignificant’ ‘Ins.’ denotes ‘insignificant’, ‘Inconcl.’ denotes ‘inconclusive’, and ‘Single st.’ denotes ‘single study’.

Table C.2.6: Income, consumption and expenditure

<u>Country</u>	<u>Study</u>	<u>PWP type</u>	<u>Treatment variation</u>	<u>PWP name</u>		<u>Overall</u>	<u>Total inc.</u>	<u>Wage empl. inc.</u>	<u>Self-empl. inc.</u>	<u>Total cons./expend.</u>	<u>Non-food cons.</u>
ETH	Sabates-Wheeler & Devereux (2010)	2	Food	PSNP		Trend +	Trend +				
CIV	Bertrand et al. (2017) - ST	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO		Trend +	Trend +	Cst. +	Trend -	Trend +	
ETH	Gilligan & Hoddinott (2007)	1		EGS		Trend +				Trend +	
SLE	Rosas & Sabarwal (2016)	1		YESP/CfW		Trend +	Trend +				
ETH	Sabates-Wheeler & Devereux (2010)	2	Mixed	PSNP		Trend +	Trend +				
GHA	Osei-Akoto et al. (2014)	1		GSOP-LIPW		Inconcl.				Trend +	Trend -
CIV	Bertrand et al. (2017) - MT	1 Plus	+ self-empl. tr.	PEJEDEC-THIMO		Mos. ins.	Cst. ins.	Cst. ins.	Trend +	Cst. ins.	
CIV	Bertrand et al. (2017) - MT	1	Only PW HHs without compl. tr.	PEJEDEC-THIMO		Mos. ins.	Cst. ins.	Cst. ins.	Trend +	Cst. ins.	
CIV	Bertrand et al. (2017) - MT	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO		Mos. ins.	Trend +	Cst. ins.	Cst. ins.	Cst. ins.	
RWA	Hartwig (2013)	1		VUP		Mos. ins.	Ins.			Mos. ins.	
ETH	Weldegebriel & Prowse (2013)	2		PSNP		Mos. ins.					
CIV	Bertrand et al. (2017) - MT	1 Plus	+ wage-empl. tr.	PEJEDEC-THIMO		Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	
MWI	Beegle et al. (2017)	1	24 workdays (harvest season)	MASAF III		Cst. ins.					Cst. ins.
MWI	Beegle et al. (2017)	1	24 extra workdays (lean season)	MASAF III		Cst. ins.					Cst. ins.
ETH	Gilligan et al. (2009a)	2	Any transfer value	PSNP		Cst. ins.				Cst. ins.	
ETH	Gilligan et al. (2009a)	2	High transfer value	PSNP		Cst. ins.				Cst. ins.	
ETH	Gilligan et al. (2009a)	2 Plus	Any transfer value + OFSP (=HABP)	PSNP + OFSP		Cst. ins.				Cst. ins.	
ETH	Sabates-Wheeler & Devereux (2010)	2	Cash	PSNP		Cst. ins.	Cst. ins.				
ETH	Tafere & Woldehanna (2012)	2		PSNP		Cst. -				Cst. -	Cst. -

Notes: 'ST' denotes 'short-term' and 'MT' 'medium-term'. 'HHs' denotes 'households', 'incl.' denotes 'including', 'compl.' denotes 'complementary', 'empl.' denotes 'employment', and 'tr.' denotes 'training'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.7: Labour supply

Country	Study	PWP type	Treatment variation	PWP name		Overall	Economic activities	Total hrs. worked	Wage empl.	(Non-farm) self-empl.	HH farm activities	Hired or shared labour
SLE	Rosas & Sabarwal (2016)	1		YESP/CfW		Cst. +			Cst. +	Cst. +		
CIV	Bertrand et al. (2016/2017) - ST	1		PEJEDEC-THIMO		Inconcl.	Trend +	Trend +	Trend +	Trend -		
ETH	Gilligan et al. (2009a)	2 (Plus)	Any transfer value	PSNP	⊗	Inconcl.			Male trend -	Trend +		
ETH	Gilligan et al. (2009a)	2 (Plus)	Higher transfer value	PSNP	⊗	Inconcl.			Male trend -	Trend +		
ETH	Gilligan et al. (2009b)	2 Plus	Agric. production enhancement services	PSNP - HVFB + OFSP	⊗	Inconcl.			Ins.			Trend -
ETH	Gilligan et al. (2009b)	2	PW only	PSNP - HVFB	⊗	Inconcl.			Ins.			Trend -
ETH	Gilligan et al. (2009b)	2 (Plus)		PSNP	⊗	Most. ins.			Cst. ins.	Most. ins.	Most. ins.	
ETH	Gilligan et al. (2009b)	Plus	Irrigation services	OFSP	⊗	Most. ins.			Ins.			Inconcl.
ETH	Gilligan et al. (2009a)	2 Plus		PSNP + OFSP	⊗	Most. ins.			Cst. ins.	Trend +		
CIV	Bertrand et al. (2016/2017) - MT	1 (Plus)	All PW HHs, incl. those with compl. training	PEJEDEC-THIMO		Most. ins.	Trend + (2016)	Ins.	Cst. ins.	Cst. ins.		
ETH	Berhane et al. (2014)	2		PSNP	⊗	Ins.				Ins.		
ETH	Berhane et al. (2011)	2 Plus	vs. no PW	PSNP + HABP	⊗	Ins.				Ins.		
ETH	Berhane et al. (2011)	2 Plus	vs. Type 2	PSNP + HABP	⊗	Ins.				Ins.		
ETH	Berhane et al. (2011)	2 Plus	vs. Plus	PSNP + HABP	⊗	Ins.				Ins.		
MWI	Beegle et al. (2017)	1		MASAF III		Ins.						Ins.
ETH	Gilligan et al. (2009b)	Plus	Agric. production enhancement services	OFSP	⊗	Cst. ins.			Ins.			Cst. ins.
ETH	Gilligan et al. (2009b)	Plus	SWC services	OFSP	⊗	Cst. ins.			Ins.			Cst. ins.
ETH	Gilligan et al. (2009b)	2 Plus	Irrigation services	PSNP - HVFB + OFSP	⊗	Cst. ins.			Ins.			Cst. ins.
ETH	Gilligan et al. (2009b)	2 Plus	SWC services	PSNP - HVFB + OFSP	⊗	Cst. ins.			Ins.			Cst. ins.
CIV	Bertrand et al. (2016/2017) - MT	1	PW only	PEJEDEC-THIMO		Cst. ins.	Ins.	Ins.	Cst. ins.	Cst. ins.		
CIV	Bertrand et al. (2016/2017) - MT	1 Plus	+ self-empl. training	PEJEDEC-THIMO		Cst. ins.	Ins.	Ins.	Cst. ins.	Cst. ins.		
CIV	Bertrand et al. (2016/2017) - MT	1 Plus	+ wage-empl. training	PEJEDEC-THIMO		Cst. ins.	Ins.	Ins.	Cst. ins.	Cst. ins.		

Notes: 'ST' denotes 'short-term' and 'MT' 'medium-term'. 'HHs' denotes 'households', 'incl.' denotes 'including', 'compl.' denotes 'complementary', 'empl.' denotes 'employment', and 'agric.' denotes 'agricultural'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.8: Food consumption and food security

Country	Study	PWP type	Treatment variation	PWP name		Overall	Food consumption	Food expenditure	Food gap	Number of meals	Food security index
ETH	Berhane et al. (2014)	2 Plus	+ compl. component	PSNP + HABP	⊗	Cst. +			Cst. +		
ETH	Sabates-Wheeler & Devereux (2010)	2	Food	PSNP	⊗	Cst. +			Cst. +		
ETH	Sabates-Wheeler & Devereux (2010)	2	Mixed	PSNP	⊗	Cst. +			Cst. +		
RWA	Hartwig (2013)	1		VUP		Cst. +		Cst. +			
GHA	Osei-Akoto et al. (2014)	1		GSOP-LIPW		Cst. +	Cst. +				
ETH	Gilligan et al. (2009b)	2	High transfer value	PSNP	⊗	Trend +	Cst. +		Trend +		
ETH	Berhane et al. (2011)	2 (Plus)		PSNP	⊗	Trend +			Cst. +	Trend +	
ETH	Gilligan et al. (2009b)	2 Plus	+ compl. component	PSNP + OFSP	⊗	Trend +			Trend +		
ETH	Gilligan et al. (2009b)	2	HVFB	PSNP - HVFB	⊗	Trend +			Cst. +		
SLE	Rosas & Sabarwal (2016)	1		YESP/CfW		Trend +	Trend +				
ETH	Gilligan et al. (2009a)	2 Plus	+ compl. component	PSNP + OFSP	⊗	Trend +	Trend +		Cst. +	Cst. ins.	
ETH	Berhane et al. (2014)	2		PSNP	⊗	Inconcl.	Cst. ins.		Cst. +		
ETH	Gilligan & Hoddinott (2007)	1		EGS	⊗	Inconcl.	Trend +				
ETH	Gilligan et al. (2009b)	2	Any transfer value	PSNP	⊗	Inconcl.	Cst. ins.		Trend +		
ETH	Porter & Goyal (2016)	2		PSNP	⊗	Inconcl.	Trend -				
ETH	Gilligan et al. (2009a)	2	High transfer value	PSNP	⊗	Most. ins.	Trend +		Cst. ins.	Cst. ins.	
ETH	Béné et al. (2012)	2		PSNP	⊗	Mos. ins.					Mos. ins.
ETH	Gilligan et al. (2009b)	Plus	OFSP irrigation services only (no PW)	OFSP	⊗	Mos. ins.					
ETH	Gilligan et al. (2009b)	Plus	OFSP seed services only (no PW)	OFSP	⊗	Mos. ins.					
ETH	Sabates-Wheeler & Devereux (2010)	2	Cash	PSNP	⊗	Cst. ins.			Cst. ins.		
ETH	Gilligan et al. (2009a)	2	Any transfer value	PSNP	⊗	Cst. ins.	Cst. ins.		Cst. ins.	Cst. ins.	
MWI	Beegle et al. (2017)	1	24 workdays	MASAF III		Cst. ins.	Cst. ins.	Cst. ins.		Cst. ins.	Cst. ins.
MWI	Beegle et al. (2017)	1	+ 24 extra workdays (lean season)	MASAF III		Cst. ins.	Cst. ins.	Cst. ins.		Cst. ins.	Cst. ins.
ETH	Tafere & Woldehanna (2012)	2		PSNP	⊗	Cst. -	Cst. -	Cst. -			

Notes: 'Compl.' denotes 'complementary'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.9: Nutrition

<u>Country</u>	<u>Study</u>	<u>PWP type</u>	<u>Treatment variation</u>	<u>PWP name</u>		<u>Nutrition overall</u>	<u>Anthro-pometry overall</u>	<u>WAZ</u>	<u>Low WAZ</u>	<u>HAZ</u>	<u>Stunting</u>	<u>WHZ</u>	<u>Wasting</u>	<u>Dietary diversity</u>
ETH	Debela et al. (2017)	1/2	FFW or CFW	FFW/PSNP	⊗	Cst. +								Cst. +
ETH	Debela et al. (2017)	1/2	FFW only	FFW/PSNP	⊗	Cst. +								Cst. +
ETH	Debela et al. (2015)	2		PSNP	⊗	Cst. +	Cst. +					Cst. +		
ETH	Porter & Goyal (2016)	2		PSNP	⊗	Trend +	Cst. +	Cst. +		Cst. +				Cst. ins.
ETH	Quisumbing (2003)	1		FFW	⊗	Mos. ins.	Mos. ins.			Mos. ins.		Mos. ins.		
ETH	Gebrehiwot & Castilla (2019)	2		PSNP	⊗	Mos. ins.	Mos. ins.			Mos. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.
ETH	Gilligan et al. (2009b)	2	Any transfer value	PSNP - HVFB	⊗	Mos. ins.	Mos. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Mos. ins.	
ETH	Gilligan et al. (2009b)	2	High transfer value	PSNP - HVFB	⊗	Mos. ins.	Mos. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	Mos. ins.	
ETH	Berhane et al. (2016)	2		PSNP	⊗	Cst. ins.	Cst. ins.			Cst. ins.	Cst. ins.	Cst. ins.	Cst. ins.	
ETH	Berhane et al. (2014)	2		PSNP	⊗	Cst. ins.								Cst. ins.
ETH	Debela et al. (2017)	1/2	CFW only	FFW/PSNP	⊗	Cst. ins.								Cst. ins.
MWI	Beegle et al. (2015)	1		MASAF III		Cst. ins.								Cst. ins.

Notes: 'FFW' denotes 'food-for-work' and 'CFW' denotes 'cash-for-work'. 'WAZ' denotes 'weight-for-age z-score', 'HAZ' denotes 'height-for-age z-score' and 'WHZ' denotes 'weight-for-height z-score'. The study by Debele et al. (2017) is classified as Type 1 in this figure although they evaluate a mix of Type 1 and Type 2 (because the evaluation period covers the time when the then existing Type 1 programmes were substituted by the Type 2 programme PSNP).

Table C.2.10: Household asset holdings

Country	Study	PWP type	Treatment variation	PWP name		Overall	Livestock	Assets (prod. and non-prod.)	Non-prod. assets	Prod. assets/capital
CIV	Bertrand et al. (2016) - ST	1 (Plus)		PEJEDEC-THIMO		Trend +		Trend +	Ins.	Trend +
RWA	Hartwig (2013))	1		VUP		Trend +	Trend +		Trend +	Trend +
ETH	Berhane et al. (2011/2014)	2 Plus	vs. no PW	PSNP + OFSP	⊗	Trend +	Trend +			Trend +
ETH	Gilligan et al. (2009b)	2	High transfer value, any variability	PSNP	⊗	Trend +	Trend +			
ETH	Gilligan et al. (2009b)	2	High transfer value, low variability	PSNP	⊗	Trend +	Trend +			
ETH	Gilligan et al. (2009b)	2 Plus	Any transfer value	PSNP + OFSP	⊗	Trend +	Trend +			
ETH	Gilligan et al. (2009b)	2	High transfer value	PSNP - HVFB	⊗	Trend +	Trend +			
SLE	Rosas & Sabarwal (2016)	1		YESP/CfW		Trend +	Trend +		Rural trend +	Rural trend +
ETH	Andersson et al. (2011)	2		PSNP	⊗	Inconcl.	Ins.			
ETH	Andersson et al. (2011)	2 Plus		PSNP + OFSP	⊗	Inconcl.	Trend +			
ETH	Berhane et al. (2014)	2 (Plus)	All PSNP recipients	PSNP	⊗	Inconcl.	Trend +			Ins.
ETH	Gilligan et al. (2009b)	2	Any transfer value	PSNP	⊗	Inconcl.	Trend +			
ETH	Gilligan et al. (2009b)	2	High transfer value, high variability	PSNP	⊗	Inconcl.	Trend +			
ETH	Sabates-Wheeler & Devereux (2010)	2	Food	PSNP	⊗	Inconcl.	Trend +	Ins.		
ETH	Tafere & Woldehanna (2012)	2		PSNP	⊗	Inconcl.			Inconcl.	
ETH	Sabates-Wheeler & Devereux (2010)	2	Mixed	PSNP	⊗	Inconcl.	Ins.	Trend -		
CIV	Bertrand et al. (2016) - MT	1	PW HHs only, excl. compl. training	PEJEDEC-THIMO		Most. ins.		Trend +	Ins.	Ins.
CIV	Bertrand et al. (2016) - MT	1 Plus	+ self-empl. training	PEJEDEC-THIMO		Most. ins.		Trend -	Ins.	Ins.
ETH	Gilligan et al. (2009b)	2	Any transfer value	PSNP - HVFB	⊗	Ins.	Ins.			
ETH	Berhane et al. (2011/2014)	2 Plus	vs. Type 2	PSNP + OFSP	⊗	Cst. ins.	Ins.			Ins.
ETH	Berhane et al. (2011)	2 Plus	vs. Plus component	PSNP + HABP	⊗	Cst. ins.	Ins.			Ins.
ETH	Gilligan et al. (2009a)	2	High transfer value	PSNP	⊗	Cst. ins.	Ins.			Ins.
ETH	Gilligan et al. (2009a)	2 Plus	Any transfer value	PSNP + OFSP	⊗	Cst. ins.	Ins.			Ins.
ETH	Sabates-Wheeler & Devereux (2010)	2	Cash	PSNP	⊗	Cst. ins.	Ins.	Ins.		
MWI	Beegle et al. (2017)	1		MASAF III		Cst. ins.			Cst. ins.	Cst. ins.
CIV	Bertrand et al. (2016/2017) - MT	1 (Plus)	All PW HHs, incl. compl. training	PEJEDEC-THIMO		Cst. ins.		Ins.	Ins.	Ins.
CIV	Bertrand et al. (2016) - MT	1 Plus	+ wage-empl. training	PEJEDEC-THIMO		Cst. ins.		Ins.	Ins.	Ins.
ETH	Gilligan et al. (2009a)	2	Any transfer value	PSNP	⊗	Trend -	Trend -			Trend -
ETH	Gilligan & Hoddinott (2007)	1		EGS	⊗	Trend -	Trend -			

Notes: 'ST' denotes 'short-term' and 'MT' 'medium-term'. 'HHs' denotes 'households', 'incl.' denotes 'including', 'compl.' denotes 'complementary', and 'empl.' denotes 'employment'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.11: Agricultural technology

Country	Study	PWP type	Treatment variation	PWP name		Overall	Farm equipment	Fertiliser use		Pesticide use	Improved seeds use	Irrigation	Technology adoption		
								Quantity	Any fertiliser used				Stone terracing	Fencing	Water harvesting
ETH	Gilligan et al. (2009b)	Plus	Irrigation services	OFSP	⊗	Cst. +		Cst. +					Cst. +		
ETH	Gilligan et al. (2009a)	2 Plus	+ compl. component	PSNP + OFSP	⊗	Trend +			Trend +		Trend +				
ETH	Hoddinott et al. (2012)	2 Plus	vs. no PW	PSNP + HABP	⊗	Trend +		Trend +					Ins.	Trend +	Ins.
ETH	Hoddinott et al. (2012)	2 Plus	vs. Type 2	PSNP + HABP	⊗	Trend +		Trend +					Trend +	Trend +	Ins.
ETH	Hoddinott et al. (2012)	2 Plus	vs. Plus component	PSNP + HABP	⊗	Trend +		Trend +					Trend +	Trend +	Ins.
CIV	Bertrand et al. (2016) - ST	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO		Trend +	Trend +								
ETH	Gilligan et al. (2009b)	2 Plus	+ irrigation services	PSNP + HABP	⊗	Inconcl.		Inconcl.					Cst. +		
ETH	Gilligan et al. (2009b)	2 Plus	+ seed services	PSNP + HABP	⊗	Inconcl.		Inconcl.					Trend +		
ETH	Gilligan et al. (2009b)	Plus	Agric. production enhancing services	PSNP - HVFB	⊗	Inconcl.		Ins.	Trend +	Ins.	Trend +	Ins.			
ETH	Gilligan et al. (2009b)	Plus	Irrigation services	PSNP - HVFB	⊗	Inconcl.		Ins.	Trend +	Ins.	Trend +	Ins.			
ETH	Gilligan et al. (2009b)	Plus	SWC services	PSNP - HVFB	⊗	Inconcl.		Ins.	Trend +	Ins.	Trend +	Ins.			
ETH	Bezu & Holden (2008)	1		FFW	⊗	Inconcl.		Most. ins.	Trend +						
ETH	Gilligan et al. (2009b)	2		PSNP	⊗	Inconcl.		Cst. ins.					Inconcl.		
ETH	Hoddinott et al. (2012)	2	vs. no PW	PSNP	⊗	Most. ins.		Ins.					Ins.	Trend +	Ins.
ETH	Gilligan et al. (2009b)	2 Plus	+ agric. production enhancing services	PSNP - HVFB	⊗	Most. ins.		Ins.	Trend +	Ins.	Ins.	Ins.			
ETH	Gilligan et al. (2009b)	2 Plus	+ SWC services	PSNP - HVFB	⊗	Most. ins.		Ins.	Trend +	Ins.	Ins.	Ins.			
CIV	Bertrand et al. (2016) - MT	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO		Ins.	Ins.								
CIV	Bertrand et al. (2016) - MT	1	Only PW HHs without compl. tr.	PEJEDEC-THIMO		Ins.	Ins.								
CIV	Bertrand et al. (2016) - MT	1 Plus	+ self-empl. tr.	PEJEDEC-THIMO		Ins.	Ins.								
CIV	Bertrand et al. (2016) - MT	1 Plus	+ wage empl. tr.	PEJEDEC-THIMO		Ins.	Ins.								
ETH	Gilligan et al. (2009a)	2 (Plus)	Any transfer value	PSNP	⊗	Cst. ins.			Ins.		Ins.				
ETH	Gilligan et al. (2009a)	2 (Plus)	High transfer value	PSNP	⊗	Cst. ins.			Ins.		Ins.				
ETH	Gilligan et al. (2009b)	Plus	Seed services	OFSP	⊗	Cst. ins.		Cst. ins.					Ins.		
ETH	Gilligan et al. (2009b)	2		PSNP - HVFB	⊗	Cst. ins.		Ins.	Ins.	Ins.	Ins.	Ins.			
ETH	Gilligan et al. (2009b)	2 Plus	+ irrigation services	PSNP - HVFB	⊗	Cst. ins.		Ins.	Ins.	Ins.	Ins.	Ins.			
MWI	Beege et al. (2017)	1		MASAF III		Cst. ins.		Cst. ins.							
RWA	Hartwig (2013)	1		VUP		Cst. ins.	Ins.				Ins.				

Notes: 'ST' denotes 'short-term' and 'MT' 'medium-term'. 'HHs' denotes 'households', 'incl.' denotes 'including', 'compl.' denotes 'complementary', 'empl.' denotes 'employment', and 'agric.' denotes 'agricultural'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.12: Agricultural production and agriculture overall

Country	Study	PWP type	Treatment variation	PWP name		Agric. product overall	Grain production output	Grain acreage	Grain yield	Agric. technology overall	Agric. overall
ETH	Gilligan et al. (2009b)	2 Plus	+ seed services	PSNP + HABP	✗	Trend +	Ins.	Trend +	Trend +	Inconcl.	Inconcl.
ETH	Gilligan et al. (2009b)	Plus	Seed services	OFSP	✗	Trend +	Trend +	Trend +	Ins.	Cst. ins.	Inconcl.
ETH	Gilligan et al. (2009b)	2 Plus	+ irrigation services	PSNP + HABP	✗	Inconcl.	Inconcl.	Cst. ins.	Cst. +	Inconcl.	Inconcl.
ETH	Gilligan et al. (2009b)	Plus	Agric. production enhancing services	PSNP - HVFB	✗	Inconcl.	Ins.	Trend +		Inconcl.	Inconcl.
ETH	Gilligan et al. (2009b)	Plus	Irrigation services	PSNP - HVFB	✗	Inconcl.	Ins.	Trend +		Inconcl.	Inconcl.
ETH	Gilligan et al. (2009b)	Plus	SWC services	PSNP - HVFB	✗	Inconcl.	Ins.	Trend +		Inconcl.	Inconcl.
ETH	Gilligan et al. (2009b)	2		PSNP - HVFB	✗	Inconcl.	Ins.	Trend +		Cst. ins.	Inconcl.
ETH	Gilligan et al. (2009b)	2 Plus	+ irrigation services	PSNP - HVFB	✗	Inconcl.	Ins.	Trend +		Cst. ins.	Inconcl.
ETH	Gilligan et al. (2009b)	Plus	Irrigation services	OFSP	✗	Inconcl.	Inconcl.	Inconcl.	Cst. ins.	Cst. +	Inconcl.
ETH	Hoddinott et al. (2012)	2 Plus	Type 2 Plus vs. Plus component	PSNP + HABP	✗	Most. ins.	Ins.	Ins.	Trend +	Trend +	Inconcl.
ETH	Gilligan et al. (2009b)	2		PSNP	✗	Most. ins.	Cst. ins.	Inconcl.	Cst. ins.	Inconcl.	Inconcl.
ETH	Hoddinott et al. (2012)	2 Plus	vs. no PW	PSNP + HABP	✗	Cst. ins.	Ins.	Ins.	Ins.	Trend +	Inconcl.
ETH	Hoddinott et al. (2012)	2 Plus	vs. Type 2	PSNP + HABP	✗	Cst. ins.	Ins.	Ins.	Ins.	Trend +	Inconcl.
ETH	Hoddinott et al. (2012)	2	vs. no PW	PSNP	✗	Cst. ins.	Ins.	Ins.	Ins.	Most. ins.	Most. ins.
ETH	Gilligan et al. (2009b)	2 Plus	+ agric. production enhancing services	PSNP - HVFB	✗	Cst. ins.	Ins.	Ins.		Most. ins.	Most. ins.
ETH	Gilligan et al. (2009b)	2 Plus	+ SWC services	PSNP - HVFB	✗	Cst. ins.	Ins.	Ins.		Most. ins.	Most. ins.
RWA	Hartwig (2013)	1		VUP		Cst. ins.	Cst. ins.			Cst. ins.	Cst. ins.
ETH	Gilligan et al. (2009a)	2 Plus	+ compl. component	PSNP + OFSP	✗					Trend +	Trend +
CIV	Bertrand et al. (2016) - ST	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO						Trend +	Trend +
ETH	Bezu & Holden (2008)	1		FFW	✗					Inconcl.	Inconcl.
CIV	Bertrand et al. (2016) - MT	1 (Plus)	All PW HHs, incl. compl. tr.	PEJEDEC-THIMO						Ins.	Ins.
CIV	Bertrand et al. (2016) - MT	1	Only PW HHs without compl. tr.	PEJEDEC-THIMO						Ins.	Ins.
CIV	Bertrand et al. (2016) - MT	1 Plus	+ self-empl. tr.	PEJEDEC-THIMO						Ins.	Ins.
CIV	Bertrand et al. (2016) - MT	1 Plus	+ wage empl. tr.	PEJEDEC-THIMO						Ins.	Ins.
ETH	Gilligan et al. (2009a)	2 (Plus)	Any transfer value	PSNP	✗					Cst. ins.	Cst. ins.
ETH	Gilligan et al. (2009a)	2 (Plus)	High transfer value	PSNP	✗					Cst. ins.	Cst. ins.
MWI	Beegle et al. (2017)	1		MASAF III						Cst. ins.	Cst. ins.

Notes: 'ST' denotes 'short-term' and 'MT' 'medium-term'. 'HHs' denotes 'households', 'incl.' denotes 'including', 'compl.' denotes 'complementary', 'empl.' denotes 'employment', and 'agric.' denotes 'agricultural'. The programme acronyms are explained in Table 2.2 on page 25.

Table C.2.13: Education

Country	Study	PWP type	Treatment variation	PWP name		Overall			(Relative) grade attainment				Enrolment	Attendance		Expenditure		Cognitive abilities	
						All children	Boys	Girls	Boys	Girls	Relative: boys	Relative: girls		Boys	Girls	Edu-cation	Vocational training	Math scores	Language scores
ETH	Berhane et al. (2015)	2 (Plus)		PSNP	X	Trend +												Cst. +	
ETH	Hoddinott et al. (2009)	2 (Plus)	Higher transfer value	PSNP	X	Inconcl.	Trend +	Most. ins.					Cst. +	Most. ins.					
ETH	Berhane et al. (2016)	2 (Plus)	High transfer value (2012)	PSNP	X	Inconcl.	Cst. ins.	Trend +	Ins.	Trend +	Ins.	Trend +	Ins.	Ins.					
CIV	Bertrand et al. (2016) - ST	1 (Plus)		PEJEDEC-THIMO		Inconcl.									Trend +	Trend -			
ETH	Favara et al. (2019)	2		PSNP	X	Inconcl.											Trend +	Cst. ins.	
SLE	Rosas & Sabarwal (2016)	1		YESP/CfW		Inconcl.						Cst. ins.	Trend -	Trend -	Most. ins.				
ETH	Tafere & Woldehanna (2012)	2		PSNP	X	Most. ins.			Most. ins.	Most. ins.									
ETH	Berhane et al. (2016)	2 (Plus)	Medium transfer value (2010)	PSNP	X	Most. ins.	Cst. ins.	Most. ins.	Ins.	Trend -	Ins.	Ins.	Ins.	Ins.	Ins.				
ETH	Berhane et al. (2016)	2 (Plus)	Low transfer value (2008)	PSNP	X	Most. ins.	Most. ins.	Most. ins.	Trend -	Trend -	Ins.	Ins.	Ins.	Ins.	Ins.				
RWA	Hartwig (2013)	1		VUP		Ins.										Ins.			
ETH	Hoddinott et al. (2009)	2 Plus		PSNP + OFSP	X	Cst. ins.	Cst. ins.	Cst. ins.					Cst. ins.	Cst. ins.					
CIV	Bertrand et al. (2016) - MT	1		PEJEDEC-THIMO		Cst. ins.									Ins.	Ins.			
CIV		1 (Plus)				Cst. ins.										Ins.	Ins.		
CIV		1 Plus	+ self-empl. tr.			Cst. ins.										Ins.	Ins.		
CIV		1 Plus	+ wage empl. tr.			Cst. ins.										Ins.	Ins.		
ETH	Hoddinott et al. (2009)	2 (Plus)	Any transfer value	PSNP	X	Cst. ins.							Cst. ins.	Cst. ins.					
ETH	Woldehanna (2009)	2		PSNP	X	Cst. ins.	Ins.	Ins.	Ins.	Ins.									
ETH	Woldehanna (2009)	1		EGS	X	Cst. ins.	Ins.	Ins.	Ins.	Ins.									

Notes: 'ST' denotes 'short-term', 'MT' 'medium-term', 'empl.' denotes 'employment', and 'tr.' denotes 'training'. The programme acronyms are explained in Table 2.2 on page 25.

3 Climate smart(er) social protection: Evidence from watershed management-focused public works in Malawi

3.1 Introduction

Finding ways to withstand shocks and adapting to changing environmental conditions has always been part of the human experience. Yet, climate change is expected to push resilience to the limit, especially in parts of the world that are already among the most vulnerable (Baarsch et al., 2020; Mendelsohn et al., 2006). There is widespread consensus that concerted efforts are necessary to strengthen climate resilience and that, despite the costs, doing so is less costly in the long run than inaction (GCA, 2019). Consequently, large parts of the development sector are in the process of mainstreaming climate change adaptation into existing development policies (Runhaar et al., 2018). Labels such as ‘climate-proof’ and ‘climate-smart’ (e.g., FAO, 2013) are visual signs of this process. The social protection sector and public works programmes (PWPs) in particular are also undergoing this mainstreaming process.

The general expectation is that safety nets strengthen the coping capacity of vulnerable people. Programmes that also allow them to save, invest, increase their skills, or diversify their income sources are expected to additionally strengthen their adaptive capacity (Beazley et al., 2016). In the conceptual studies on the nexus of social protection and climate resilience, PWPs are heralded as a social protection instrument with a particularly large potential to strengthen climate resilience if they create climate-smart community assets (asset vector) and climate-smart practices are learned on-the-job or off-the-job (skills vector) (Aleksandrova, 2019; Béné, 2011; Béné et al., 2014; Costella et al., 2021; Davies et al., 2013; ILO, 2015; Kuriakose et al., 2013; Schwan & Yu, 2018). Both the community assets and the new skills may also benefit the wider community beyond the PW participants. In this paper, the label *climate-smart* is attached to activities that set out to strengthen climate resilience, whereas contributions to climate change mitigation are not considered a necessary condition.

The world’s largest PWP is the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) in India and Africa’s largest PWP is the Productive Safety Net Programme

(PSNP) in Ethiopia. Both programmes follow an integrated watershed management approach (McCord & Paul, 2019; Woolf et al., 2018; World Bank, 2013), which is widely viewed as a key strategy to strengthen climate resilience (Gebregziabher et al., 2016; Joosten & Grey, 2017).¹⁸ As a result, they are counted among the largest climate change adaptation programmes in the world (European Commission, 2018). While their impact on climate resilience is still only partly understood, there are insightful studies that highlight the benefits, potential, and limitations of PWPs in this respect (Adam, 2015; Andersson et al., 2011; Esteves et al., 2013; Fischer, 2019; Gazeaud & Stéphane, 2020; Godfrey-Wood & Flower, 2018; Kaur et al., 2019; Ravindranath et al., 2013; Steinbach et al., 2016; Weldegebriel & Prowse, 2013; Woolf et al., 2018). However, none of these studies compare empirically whether design changes to make existing programmes climate-smarter succeed in doing so. They also do not disentangle the role of and benefits for non-PW participants. With the notable exception of Ignaciuk et al. (2021), quantitative studies from PWPs outside of India and Ethiopia do not seem to exist to date either. This paper addresses these gaps with empirical evidence from Malawi. I use a quasi-experimental study design to analyse how a PW model that aims to enhance the impact on climate resilience (enhanced model hereafter) performs in this respect compared to the regular approach of Malawi's largest PWP (standard model hereafter) over a period of 24 months. The work activities in both models focus on watershed management practices, such as soil and water conservation (SWC) and afforestation. The main differences between the two models are the following: In the enhanced model, work activities are embedded in a communal watershed management plan, more spatially concentrated, and attempt to not only rely on paid PW labour but to also mobilise further voluntary labour contributions from the community. Moreover, the enhanced model adds capacity building activities aimed at promoting knowledge about and adoption of watershed management and other climate-smart practices.

Using a difference-in-differences approach, I investigate whether the two PW models differed in their contributions to climate resilience. Specifically, the outcomes of interest are household level indicators for voluntary labour input to watershed management-related community work as well as adoption of climate-smart agricultural and conservation practices by people on their private land. These are intermediate short-term indicators that can contribute to strengthening

¹⁸ MGNREGA was not conceived as a dedicated climate change adaptation programme, but since 2016 65% of the programme expenditure must be spent on natural resource management and water-related expenditure (McCord & Paul, 2019). Likewise, PSNP's focus on watershed management increased over time (Woolf et al., 2018).

climate resilience in the long-term. Two-period panel data were collected from households in four clusters (catchments hereafter) where the implementation of the standard model had started in early 2016. One of these catchments was purposely chosen to switch to the enhanced model (treatment catchment hereafter) in early 2017, whereas the standard model continued to be implemented in the other three catchments (control catchments hereafter). The control catchments were purposely selected based on their similarity to the treatment catchment. In each catchment, approximately half of the randomly selected sample comprises households who participated in the PWP at the time of the baseline survey and the other half of households who did not participate in the PWP at the time. This allows for heterogeneity analysis by PW status, which is another key contribution of this paper. The decision which households got to participate in the PWP was determined by the regular targeting process prior to the start of the standard model. Thus, it was not randomly assigned.

The main results are as follows. Compared to the standard model, the enhanced model led to an increase in the voluntary labour contributions to community watershed management, specifically regarding land conservation, afforestation, and seedling production in nurseries (nursery hereafter). This increase is mainly driven by PW participants, but non-PW participants also made substantial contributions. These labour contributions do not come at the expense of other communal work. Moreover, the additional emphasis on capacity building and skills transfer in the enhanced model led to a small increase in the adoption of climate-smart practices by households on their private land, specifically drainage, box ridges, and manure. These findings imply that making modest changes to the work activities to align PWPs to the principles of watershed management and putting more emphasis on capacity building can make PWPs climate-smarter. In particular, such changes can broaden the impacts of the PWP beyond the group of PW participants to the wider community.

First and foremost, this paper contributes to the literature on the role of social protection, specifically PWPs, for strengthening climate resilience (Adam, 2015; Andersson et al., 2011; Esteves et al., 2013; Fischer, 2019; Gazeaud & Stéphane, 2020; Godfrey-Wood & Flower, 2018; Kaur et al., 2019; Ravindranath et al., 2013; Steinbach et al., 2016; Weldegebriel & Prowse, 2013; Woolf et al., 2018). Additionally, it adds to the literature on collective action in the context of watershed management (Agrawal et al., 2015; Reichert, 2014; T. A. White & Runge, 1995), environmental conservation through payment for eco-system services schemes (Alix-Garcia et al., 2019; Neuteleers & Engelen, 2015a; Popa, 2015; Rode et al., 2015), and

social protection programmes (Adato, 2000; Attanasio et al., 2015; Evans et al., 2019; Loewe et al., 2020). Lastly, it contributes to the literature on technology adoption in the context of PWPs and/or communal watershed management (Gebremedhin & Swinton, 2003; Hagos & Holden, 2006; Ignaciuk et al., 2021).

The rest of the paper is structured as follows. Section 2 presents the study context and interventions under investigation. Section 3 describes the data and methods used for the evaluation. Section 4 presents and discusses the results. Section 5 concludes.

3.2 Study context and interventions

3.2.1 Conceptual link between PWPs and climate resilience

In this paper, I use the framework by Beazley et al. (2016) because it highlights those contributions to climate resilience that set PWPs apart from other social protection instruments more prominently than alternative frameworks (Aleksandrova, 2019; Béné, 2011; Béné et al., 2014; Costella et al., 2021; Davies et al., 2013; Kuriakose et al., 2013; Schwan & Yu, 2018). In their framework, climate resilience is a function of coping capacity and adaptive capacity that both can be strengthened through three vectors, namely the wages paid, assets created, and skills conveyed.¹⁹ Coping capacity describes the capacity to withstand and recover after a (climate) shock has occurred. Adaptive capacity relates to the ability to adjust to potential damage through prevention and learning from past (climate) shocks. Like the other frameworks, it emphasises not only mechanisms specific to climate resilience but also considers the role of mechanisms that strengthen resilience in a broader sense. I apply the label *climate-smart* in this paper to activities that set out to strengthen climate resilience.²⁰ Typical examples of climate-smart activities in the context of in this paper are soil and water conservation (SWC) techniques and generally activities related to integrated watershed management (Fontes, 2020; Joosten & Grey, 2017).

¹⁹ Other frameworks of resilience are more complex. For example, Bahadur et al. (2015) distinguish between adaptive capacity, anticipatory capacity, and absorptive capacity.

²⁰ According to the definition of the FAO (2021), activities are considered climate-smart if they contribute to these three objectives: 'sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions, where possible'. Hence, my use of the label *climate-smart* is different as it does not make the third objective of the FAO definition a necessary condition.

The wage vector subsumes mechanisms that are linked to the wage that is paid for working in a PWP. Most wage-related mechanisms that strengthen coping capacity or adaptive capacity are not specific to climate resilience. Exceptions are if wages enable investments in climate-smart technologies or diversification into livelihood activities that are less exposed to climate shocks. The asset vector comprises mechanisms linked to the creation of climate-smart communal assets or the provision of climate-smart services. The skills vector includes all forms of learning climate-smart techniques in the context of PWPs, both on-the-job (learning-by-doing) and off-the-job (directly or indirectly). Indirect benefits may arise when non-PW participants observe or learn from PW participants. Due to the characteristics of the PW models that I empirically compare, this paper focuses on mechanisms that aim to strengthen adaptive capacity through the asset vector and skills vector. In what follows, I first describe PW in the Malawian context and then the specific PW models of interest.

3.2.2 Public works in Malawi

Malawi has always been prone to extreme weather events such as droughts and floods and it is expected that climate change will further aggravate this risk (IPPC, 2014; Pauw et al., 2011). In fact, the country had experienced two consecutive poor agricultural seasons in the years before the study period so that 6.5 million of its around 18 million people suffered from food shortages at the time of the baseline survey (World Bank, 2016). As a means to improve the food security of poor households with excess labour capacity, PWP have been implemented in Malawi since the mid-1990s when the PWP under the Malawi Social Action Fund (MASAF) started. The MASAF PWP has been the largest social protection programme for the working age population in the country ever since. The fourth phase of this programme (MASAF-4 PWP), in this paper called standard model, serves as the counterfactual in this paper. Funding for the PWP comes mainly from the World Bank, but it is implemented through government structures. The MASAF-4 PWP has not been rigorously evaluated, but several studies assess previous phases (e.g., Bloom et al., 2005; Chirwa, Zgovu, & Mvula, 2002). In particular, Beegle, Galasso and Goldberg (2017) evaluated the effect of the MASAF-3 PWP on food security in a randomised controlled trial. Like the MASAF-4 PWP, it offered a maximum of 48 workdays

per year. The study concentrates solely on the wage vector and finds no evidence that the programme made participants more resilient.²¹

Partly in response to these sobering findings, several changes were made in the MASAF-4 PWP. Targeting moved from an ad-hoc approach to three-year cycles. In combination with scale-ups to broaden coverage in the wake of severe covariate shocks, these changes were meant to increase the programme's effect on households' resilience. In awareness of the harmful effects of environmental degradation and extreme weather shocks, MASAF-4 shifted the work focus from traditional infrastructure towards watershed management-related activities. These were the main changes to make the PWP climate-smarter. However, the remaining differences between this programme and the international flagship programmes like PSNP and MGNREGA are apparent. In terms of employment, India's MGNREGA offers one hundred workdays per person per year on demand. Ethiopia's PSNP offers 72 workdays per year to those targeted for at least five years and has in-built financial reserves to broaden coverage in crisis situations. In terms of community asset creation and skills transfer, both countries have many years of experience in participatory community-driven watershed management, unlike Malawi (Chimdesa, 2016; Kerr, 2002). The rationale of the enhanced model evaluated in this paper is to adapt the standard model by adding some features from the international flagship programmes that pertain to the asset vector and skills vector, while leaving the wage vector unchanged. The Malawian Ministry of Finance, Economic Planning and Development, supported by the GIZ and in cooperation with the Mchinji District Council, implemented the enhanced model as a pilot project.

3.2.3 Contrasting the enhanced model and standard model

Commonalities: The MASAF-4 PWP is allocated to catchments²² using nation-wide pro-poor geographic targeting. Funding is allocated to each district in proportion to population size and poverty levels. District officials then use the same criteria to target a subset of catchments in their district. Targeting of PW participants in a catchment combines community-based targeting and self-selection. There are usually several group village headmen per catchment and each of

²¹ In particular, the linkage between the PWP and Malawi's nation-wide Farm Input Subsidy Programme (FISP) did not increase access of fertiliser. The rationale behind this linkage was that the income from PW cycles during the planting season would allow even poor households to redeem the voucher because the transaction costs and the modest co-payment become affordable.

²² Since MASAF-4, the focal areas of the PWP are called catchments. However, contrary to what the name implies, their boundaries are usually more determined by social and administrative criteria than by hydrological criteria. This is common in watershed/catchment management (Swallow et al., 2002).

them oversees three to ten villages (Beegle et al., 2017). The headman decides, based on the available funding, how many households participate in the villages. In cooperation with the village committees, the headman then selects the participating households, whereby poor households with unused labour capacity are expected to be prioritised.²³

The envisaged minimum enrolment duration of a household is three years. Hence, households that were enrolled at the launch of the MASAF-4 PWP in early 2016 were expected to remain enrolled at least until the end of 2018. The programme aims to offer 48 paid workdays per household per year. Usually, these workdays are split into two 24-day cycles. The daily wage rate is pegged to the national minimum wage. In 2016, it was 600 Malawi Kwacha per day and in the second half of 2018 it was increased to 900 Malawi Kwacha. These rates correspond to around 1 Euro. Officially, a workday in the PWP has four hours and thus leaves participants room for other activities. Payment delivery mechanisms are identical in both models.

Differences: The key changes of the enhanced model compared to the standard model aim at embedding the PWP in a communal watershed management plan, following the guidelines on integrated watershed management more strictly, strengthening capacity building related to it, and broadening the outreach of all activities to non-PW households.

The enhanced model sets out to complement the PW cycles of the standard model with recurrent *watershed management-related community work* for which voluntary unpaid labour from PW households and non-PW households is to be mobilised. The rationale is that the volume and timing of PW labour in the standard model are insufficient to effectively implement watershed management in environmental hotspots and, thus, inadequate to strengthen climate resilience. Watershed management-related community work is therefore the first outcome area of interest in the empirical analysis. Both community works and PW mainly took place on communal land, but sometimes also on private land that is in a zone of the catchment where SWC measures are needed for effective integrated watershed management.

The capacity building strategy of the enhanced model (*enhanced capacity building* hereafter) at the catchment level aims to promote knowledge and the adoption of climate-smart techniques in line with the principles of integrated watershed management. The methods for dissemination comprise on-the-job training (i.e., during PW or community work), demonstration sessions for

²³ The selection criteria were vague. There were no clear guidelines how to measure and rank the poverty levels of households in the targeting process.

manure making, home visits, the screening of educational videos during community meetings (showing best-practice examples of communal watershed management from Ethiopia). By contrast, under the standard model, there is no coherent or concerted capacity building strategy. If anything to that end takes place in the control catchments, it is not by design. Adoption of climate-smart practices is therefore the second outcome area of interest in the empirical analysis.

Communities under the standard model were also encouraged to focus more on watershed management-related activities like SWC and afforestation than in previous phases of the MASAF PWP, but other activities that were typical for past PWP phases, for example road works, were still permissible. The priorities and activities were written down in a catchment-level action plan. Most catchments under the standard model were much bigger than guidelines on watershed management recommend. Therefore, the treatment catchment was subdivided into several micro-catchments that became the main implementation level. Each micro-catchment set up its own micro-catchment committee and developed its own action plan. Unlike in the standard model, the development of the action plans was facilitated by an external watershed management expert and action plans not only cover activities to be implemented using the paid PW labour of the MASAF-4 PWP but also additional voluntary community work.²⁴ For the micro-catchment committees, which do not exist in the standard model, a central role was foreseen in organising and supervising the watershed management-related community work and knowledge dissemination, in close collaboration with the government extension workers.

Lastly, it must be noted that the micro-catchments in the treatment catchment received a small extra support package of tree seedlings and a few basic tools (e.g., wheelbarrows) in 2017 to bridge a temporary shortfall of such inputs being provided through the implementation structures of the standard model. The control catchments faced the unabated shortfall.²⁵

²⁴ In addition, each micro-catchment developed environmental bylaws to specify practical rules for a more sustainable use of natural resources. Their effects are not further discussed in this paper.

²⁵ I discuss the implications of this difference for the internal and external validity of my empirical results in Section 0.

3.3 Data and methods

3.3.1 Empirical approach

I use a difference-in-differences (DiD) approach to investigate whether the enhanced model differs from the standard model regarding contributions to climate resilience after 24 months. Two-period panel data were collected from households in four catchments where the implementation of the standard model had started in early 2016. The treatment catchment was purposely chosen by the implementers to switch to the enhanced model in early 2017, whereas the standard model continued to be implemented in the three control catchments.²⁶ I measure contributions to climate resilience through household level indicators for voluntary labour input to watershed management-related community work and the adoption of climate-smart practices on households' private agricultural land. I focus on these intermediate measures of climate resilience instead of ultimate outcomes (such as exposure to and effects of shocks, productivity, and food security) because it is unrealistic that differences in ultimate outcomes would have manifested after only two years. I describe the dependent variables in more detail in Section 3.3.4.

The internal validity of the DiD approach relies critically on the assumption that households in treatment and control catchments were on parallel trends for the variables of interest prior to the launch of the enhanced model and would have remained on parallel trends without the introduction of the enhanced model. Therefore, the three control catchments were purposely chosen with the help of a watershed management expert to maximise comparability to the treatment catchment.²⁷ To check whether this was successful I conduct balancing tests on a wide range of variables (see Section 3.3.4). Moreover, I explore descriptively whether there were any differential developments during the evaluation period (i.e., between baseline and endline) that affect the outcomes but are not due to the enhanced model and, thus, could invalidate the parallel trends assumption (see Section 3.4.4).

Three distinct types of participation play a role for the empirical approach in this paper: PW participation, participation in voluntary community work, and participation in enhanced capacity building activities.

²⁶ Due to financial constraints the number of treatment catchments could not be increased to more than one. Not more than three control catchments were chosen for the same reason, but also because the added value of having more control catchments is limited when there is only one treatment catchment.

²⁷ See the list of criteria in Appendix 3.A: Survey locations and selection criteria.

PW participation denotes whether a household member was enrolled in the MASAF-4 PWP and, thus, received payment for labour during the official PW cycles. The decision which households got to participate in the PWP was the outcome of the regular targeting process (described in Section 3.2.2) prior to the start of the standard model. Hence, it was unrelated to this evaluation and not randomly assigned. In each catchment, the randomly selected sample of households was stratified by PW status, such that half of it comprised of households participating in the PWP at the time of the baseline survey and the other half of households not participating in the PWP at that time.

Participation in *community work* denotes whether a household member contributed voluntary unpaid labour to collective community work. I further distinguish between watershed management-related community work, which is one of the outcomes expected to be affected through the enhanced model, and other community work such as upgrading school buildings or maintaining roads.

Participation in *enhanced capacity building activities* is specific to the treatment catchment and denotes to what extent a household attended one of the many capacity building activities aimed at promoting knowledge about and adoption of climate-smart or watershed management-related practices (discussed further in Section 3.4.1).

Neither participation in the watershed management-related community work nor participation in the enhanced capacity building activities was random. Each household could decide freely about participation, but everybody was encouraged and especially PW households were expected to participate. Moreover, community-minded households, households that consider the environmental challenges in the area as more severe, or households keener on learning about watershed management may have been more inclined to participate. Participation of non-PW households may also have been strategic if it was regarded as a way to increase one's chances of getting enrolled in the PWP. In fact, key informants reported that this behaviour was relevant in some villages, especially for the community work (Beierl & Grimm, 2018).

Having defined the three forms of participation, I further explain their respective role in my empirical approach. I estimate intent-to-treat (ITT) effects of the enhanced model on the outcomes by proxying treatment with a binary variable that denotes whether a household lives in the treatment catchment. If the parallel trends assumption holds, the ITT estimates show the average impact of the modifications of the enhanced model, regardless of actual participation in the extra activities it offered, compared to the average effect of the standard model in the

control catchments. The advantage of the ITT estimates is that, unlike treatment-on-the-treated (TOT) effects, they are not sensitive to endogenous factors driving variations in the outcomes of interest, namely participation in watershed management-related community work and the adoption of climate-smart practices. However, the downside is that ITT effects tend to be much smaller than TOT effects and to, hence, underestimate the true effects quite considerably. Therefore, I additionally use an instrumental variables (IV) approach in which I instrument a dummy denoting participation in the enhanced capacity building activities with the treatment catchment dummy to identify TOT effects that are unlikely to suffer from endogeneity under certain assumptions (further discussed in Section 3.3.5). Moreover, taking advantage of having both PW households and non-PW households in my sample, I study heterogeneity of impacts by PW status through DiD specifications for subsamples for each PW status. In what follows, I describe the data and methods in more detail.

3.3.2 Data collection

The treatment catchment is in Mchinji district, close to the border with Zambia, and approximately a three-hour drive away from Malawi's capital Lilongwe. One control catchment was chosen from Mchinji District and the two other control catchments from the neighbouring Kasungu District.²⁸

In 2016, two work cycles of the standard MASAF-4 PWP took place in all four catchments. The baseline survey was conducted in February 2017, which is one year after the launch of the standard model but before the treatment catchment switched to the enhanced model. Apart from one initial community meeting, no activity related to the enhanced model had taken place before the baseline survey. February is the middle of the rainy season and almost the peak of the 'hunger season' in the survey locations. Hence, it is the period when most farmers, namely those who rely on rain-fed farming, have finished planting and are preparing for the harvest of maize, the main staple crop, in April.

924 households were sampled in total; 308 from the treatment catchment and the remaining 616 from the three control catchments. The number of households sampled per control catchment varied in proportion to the population size. In each catchment, sampling was stratified on

²⁸ Catchments from the neighbouring district were included because the enhanced model foresaw capacity building for district officers and extension in Mchinji and having control catchments from another district allows accounting for intra-district spillovers of district-level activities. Due to space constraints, intra-district spillovers are not further analysed in this paper. If they exist, I underestimate the impacts of the enhanced model with my empirical approach.

whether the household was enrolled in the standard PWP at the time of the baseline survey. The aim was a fifty-fifty ratio between PW households and non-PW households.²⁹ One of the four villages in the treatment catchment did not have a PW project during the first year of the PWP and, therefore, only non-PW households were sampled there.³⁰ The other three villages had a PW project on afforestation, land management, and irrigation, respectively. In most locations, the sampling was done using the random-walk method, except for a few small villages where up-to-date household lists were available to randomly sample from.

The main survey instrument was a structured household questionnaire. Basic household information on demography, health, education, housing conditions, food security, livelihood activities, financial inclusion, asset ownership, sources of income and support, agricultural information, exposure to extension services, as well as shocks and coping mechanisms were collected. In the endline survey, the questionnaire was extended to capture participation in the various components of the enhanced model.³¹

The endline data were collected two years after the baseline data and in the same month to ensure that seasonal variation does not bias the responses. Of the 924 respondents interviewed at baseline, 771 respondents could be re-interviewed. This corresponds to an attrition rate of 16.6%. There are two noteworthy differences between attrited and non-attrited households. First, attrition rates in the Kasungu catchments are higher than in the Mchinji catchments (21.2% vs. 12.4%). Second, attrition rates in all control catchments are higher for non-PW households than PW households (25.0% vs. 12.2%), but similar in the treatment catchment (12.8% vs. 11.7%). According to key informant interviews conducted at the time of the endline survey, both differences can in part be explained by the fact that the baseline sample in the Kasungu catchment comprised of quite a few people who had just temporarily moved to the area and who had left again by the endline. Most of these people had not been PW participants at baseline. These explanations suggest that using the balanced sample as the basis for the analysis, if anything, improves comparability between the treatment catchment and the control

²⁹ In the two catchments with clearly separable villages of similar population size, sampling was additionally stratified at the village level. Hence, in a catchment with n villages, $1/n^{\text{th}}$ of the catchment-wide quota was sampled per village.

³⁰ This one village did not have a PW project because only a limited number of projects can be awarded to a catchment and environmental hotspots were to be prioritised. The official explanation is that the uncovered village was deemed as less affected by environmental degradation, but local politics may also have played a role.

³¹ In addition, qualitative information was collected through in-depth interviews with a random subsample of baseline respondents, focus group discussions with project committees, and key informant interviews with extension workers and district officers (Beierl & Grimm, 2018).

catchments. Therefore, the entire analysis in this paper is based on the balanced sample that does not include the baseline observations of the attrited households.³²

3.3.3 PW status

Despite the official guideline to keep the same households on the MASAF-4 PWP for three years (2016-2018), there has been considerable movement in and out of the programme between baseline and endline. Moreover, an unexpected ad-hoc work cycle under a different PWP, the Input for Assets (IFA) programme,³³ took place in the village with no previous MASAF-4 PW project in the treatment catchment (*special village* hereafter). Hence, there are multiple ways to classify the PW status of households. Table 3.1 summarises the main dynamics.

Table 3.1: PW groups in the sample

	Treatment catchment						Control catchments	
	All villages		Special village		Other villages			
	(1)	(2)	(3)	(4)				
Never-PW	102	(0.38)	28	(0.44)	74	(0.36)	187	(0.37)
Always-MASAF-4	88	(0.33)	0	(0.00)	88	(0.43)	235	(0.47)
MASAF-4 Dropout	24	(0.09)	2	(0.03)	22	(0.11)	31	(0.06)
MASAF-4 Entrants	18	(0.07)	0	(0.00)	18	(0.09)	44	(0.09)
IFA/Other Entrants	36	(0.13)	34	(0.53)	2	(0.01)	3	(0.01)
Observations	268		64		204		500	

Notes: The last row presents the total number of households in the balanced panel from the respective location. The remaining rows present the size of five PW groups that have been classified based on their combined PW status at baseline and endline. In parentheses are the fractions that these groups constitute in reference to the total observations per column.

As per the sampling strategy, approximately half of households were enrolled in MASAF-4 at baseline. Taking the PW status both at baseline and endline into account leads to five groups. *Never-PW* household refers to those who were neither enrolled in a PWP at baseline nor at endline. *Always-MASAF-4* households refers to those who were continuously enrolled in the MASAF-4 PWP. *MASAF-4 Dropouts* denotes households that were enrolled at baseline but no longer at endline and *MASAF-4 Entrants* denotes households that were not enrolled at baseline but at endline. *IFA/Other Entrants* refers mainly to the 34 households from the special village who participated in the IFA cycle, but also to a few exceptional households from other locations that got access to a non-MASAF PWP. Together, entrants and dropouts are classified as

³² See Appendix 3.B: Attrition test results for a more detailed attrition analysis.

³³ In late 2017 and early 2018 one work cycle under the IFA component of the Malawi Floods Emergency Recovery Project (MFERP) took place in this village and offered short-term employment (24 workdays of four hours per day, spread over four weeks) for 100 villagers. 34 of them are in our sample. As payment, each worker received 50 kg of urea fertiliser and 10 kg of Monsanto hybrid maize seeds. The imputed value of this package considerably exceeds the MWK 14,400 that a worker earned for 24 days through the MASAF-4 PWP at the time.

switchers because they have in common that their PW status changed between baseline and endline.

In my preferred specifications, I concentrate on Always-MASAF-4 households and Never-PW households, and do not consider the switchers. Never-PW households make up 38% of the sample in the treatment catchment and 37% in the control catchments. Always-MASAF-4 households constitute 33% in the treatment catchment and 47% in the control catchments. Hence, the main empirical analysis is based on a panel of 612 households that comprises 289 Never-PW households and 323 Always-MASAF-4 households. Hereafter, PW household refers to Always-MASAF-4 and non-PW household to Never-PW. As robustness tests (available upon request), I checked that results are neither sensitive to the choice of PW group nor to the inclusion or exclusion of the special village.

3.3.4 Dependent variables and baseline balance tests

One condition for getting unbiased effects in a DiD design is that the treatment group and control group were on parallel trends before the treatment catchment switched to the enhanced model. With only one data point per household from the pre-intervention period, I cannot directly check parallel trends, but I take similarities in pre-intervention levels as supporting evidence that trends are also similar. For the dependent variables and other household characteristics, I compare baseline characteristics of households who reside in the treatment catchment with households from the control catchments. Additionally, I do the same tests separately for the subsamples of PW households and non-PW households.

The baseline summary statistics for the dependent variables and control variables are presented in Table 3.2 and for additional household characteristics in Table E.3.12 of Appendix 3.E: Additional baseline summary statistics. Columns 1 and 2 in Table 3.2 display the means of PW households and non-PW households in the control catchments, respectively. For non-binary variables, the standard deviation is additionally reported below in parentheses. Columns 3 to 5 show differences in means.³⁴

My dependent variables for the asset vector indicate the number of voluntary unpaid community workdays in the past twelve months in three watershed management-related sectors: land conservation, afforestation, and nursery activities. In addition, I consider the total number of

³⁴ In Appendix 3.E: Additional baseline summary statistics, I additionally report these summary statistics without observations from the special village.

workdays aggregated across all sectors, including sectors not related to watershed management (mainly roads and schools), in order to explore crowding effects.³⁵ In my preferred specifications, these dependent variables are winsorised at fraction 0.98 to avoid distortions by outliers. Table 3.2 shows that watershed management-related community work was extremely rare in all catchments at baseline. Additionally, I present summary statistics for community work overall and in other sectors because baseline differences there could be indicative of systematic differences in the willingness to cooperate for the common good and, thus, threaten comparability. Table 2 shows, however, that community work was overall equally common at baseline. Around half of the households had contributed at least one workday in the previous year in any sector, mostly concentrated on road and school-related activities. In terms of the overall number of workdays, non-PW households in the treatment catchment contributed somewhat less than the non-PW households in the control catchments (2.5 days difference).

For the skills vector, I focus on the adoption of SWC measures by households on their private land. Given that the SWC measures are meant to prevent soil erosion and/or to retain moisture, they are climate-smart in the sense that they can strengthen climate resilience (Fontes, 2020). If the standard model were to increase the adoption of climate-smart practices, I expect that it would be mainly through on-the-job learning during the PW cycles and concentrated on PW households, in line with what Gebremedhin and Swinton (2003) find for food-for-work activities in Ethiopia. In addition, there could be spillovers to non-PW households if they observe the PW activities. The enhanced model offers PW households and non-PW households two additional channels to increased adoption, namely through on-the-job learning during the community works or off-the-job learning through the enhanced capacity building activities. Lastly, as noted in Section 3.2.3, new SWC measures on private land can also be the outcome of PW and community work on that land. In my analysis of SWC adoption, I try to distinguish this asset vector-related channel from the skills vector-related channels. Specifically, I use the number of SWC measures on the households' land, the number of days worked on SWC on one's land in the last twelve months, a binary variable that denotes whether the household has any SWC measures on its land, and five binary variables for the presence of specific SWC measures (grass strips/barriers; drainage/ditches/swales; contour bunds; marker ridges; and box

³⁵ Note that a workday in the questionnaire was not defined as a certain number of working hours. Instead, respondents were asked to report the number of days on which they contributed some work. I have no reason to believe that the average number of working hours per day differed systematically by PW status or location. Otherwise, this could have biased results. For a detailed account of the underlying survey questions and how the indicators used in this paper were created based on them, see Table F.3.13 in Appendix 3.F: Survey questions.

ridges).³⁶ These types of SWC measures are implemented through the land conservation subprojects of the PWP not only in the treatment catchment but also the control catchments. Lastly, I include a binary variable denoting whether the household used manure in the last twelve months. Unlike the other SWC measures, the techniques for making and applying manure were not promoted on-the-job during PW or community work but through off-the-job demonstration sessions in the enhanced model. In the standard model, the promotion of manure was not specifically foreseen.

Table 3.2 shows some baseline differences in individual SWC adoption between the treatment and control catchments. Overall, SWC measures are somewhat less common in the treatment catchment and this difference is primarily driven by non-PW households. While three quarter of households in the treatment catchment have at least one SWC measure on their land, this is 8 pp below the levels in the control catchments. For non-PW households, the gap is 12 pp. The number of SWC measures is 0.25 measures lower overall and 0.33 measures lower for non-PW households. Households in the treatment catchment also worked, on average, 2.04 workdays less on SWC measures in the past twelve months. With respect to specific SWC measures, grass strips as barriers are less common in the treatment catchment (-12 pp). Drainage is also less common but only for non-PW households (-7 pp). By contrast, contour bunds are more common among PW households in the treatment catchment than among PW households in the control catchments (-15 pp). Differences regarding the other SWC measures are not statistically significant. The differences in the use of manure particularly stand out. In the last twelve months, 22% of households in the treatment catchment applied manure, which is 24 pp below the usage rate in the control catchments. In this case, the gap is even larger for PW households (-28 pp) than for non-PW households (-18 pp). In part, this difference may be due to manure being used as substitute for fertiliser because fertiliser use among PW households in the treatment catchment was also higher than in the control catchments (+13 pp). Irrespective of the reason, there was clearly a lot of catch-up potential in manure use in the treatment catchment prior to the start of the enhanced model. Generally, the differences regarding the dependent

³⁶ Contour bunds follow the contour of the slopes and crops are to be planted on them. Marker ridges 'mark' the gap between two contour bunds. Box ridges are partitions between contour bunds to hold water and prevent erosion occurring in parallel with the ridges. The category *drainage* comprises swales and other forms of trenches. Their purpose is to trap washed out soil and, at the same time, to maintain soil moisture. Grass barriers, especially vetiver grass, stabilise soil can also protect against weeds and pests. (Chigwiza & Kanazawa, 2008)

For a detailed account of the SWC-related survey questions and how the indicators used in this paper were created based on them, see Table F.3.14 in Appendix 3.F: Survey questions.

variables of the skills vector underline the importance of controlling for these when estimating the DiD specifications.

The summary statistics for other key household characteristics displayed in Table 3.2 and the additional ones in Table E.3.12 of Appendix 3.E: Additional baseline summary statistics show that the profiles of households in the treatment catchment are overall quite comparable to those in the control catchments. The demographic composition, health profile, and education levels of the households are similar, except for the slightly larger household size (+0.5 members) in the treatment catchment.

Almost all households are engaged in farming and 77% rely primarily on farming for their livelihood. Often, household farming is complemented by income from agricultural piecework (*ganyu*), which is the most common coping mechanism in Malawi. Fewer people in the treatment catchment relied heavily on *ganyu* in the previous twelve months (-8 pp). This may reflect the lower food insecurity in the treatment catchment at that time (food gap smaller by 1.2 months), probably partly due to the lower exposure to the preceding drought (-18 pp). The potentially problematic implications of this difference on comparability are somewhat mitigated by the fact that the control catchments received more food support through the national emergency response (-25 pp) and more people benefitted from the distribution of subsidised fertiliser (-9 pp). More people in the treatment catchment engage in simple forms of irrigation farming during the dry season (+12 pp). This may be another reason why households in the treatment catchment are not as reliant on *ganyu*. Wage employment is rare everywhere but slightly less common in the treatment catchment (-5 pp). There are no indications of substantial systematic differences in wealth levels, as proxied by ownership of durables, productive assets, quality of housing, and agricultural land size.

Soil erosion appears to be an equally common problem in all catchments. Around four in five households report to experience at least some soil erosion on their agricultural land, and one in five even on their entire land. Considering that the mitigation of soil erosion is one of the main objectives of watershed management, there is a good chance that the watershed management activities promoted through both PW models are in heavy and equal demand among the local population.

Overall, the differences highlighted in this section require controlling for baseline differences in the analysis because in some cases they might moderate or confound the effects of the investigated PW models. Community work and the adoption of new agricultural or SWC

practices are both labour-intensive activities without (guaranteed) immediate economic return. Participation in such activities is likely to be contingent on a household's labour capacity, reliance on household farming, and the absence of acute distress. Therefore, I control for household size, age of household head, disability/chronic illness of head or spouse, employment or business status, and food insecurity measured by the food in the last 12 months. In addition, I control for marriage status, highest education level obtained by head or spouse, as well as the quantity of productive and domestic assets owned.

Table 3.2: Baseline summary statistics and balancing tests, dependent variables and control variables

	Mean in control catchments (sd)		Difference in means (C-T)		
	PW (1)	Non-PW (2)	PW (3)	Non-PW (4)	Both (5)
Asset vector: voluntary community work, last 12 months					
At least one workday in ...					
Any sector	0.60	0.52	0.09	0.08	0.09*
Afforestation	0.04	0.02	0.03	0.02	0.03
Land conservation	0.02	0.01	-0.01	0.00	0.00
Nursery/seedling production	0.01	0.00	0.01	0.00	0.00
Road construction/maintenance	0.05	0.05	-0.21**	-0.11**	-0.16**
Other activities	0.38	0.37	0.18**	0.13*	0.15**
Number of community workdays in ...					
Total	6.47 (12.2)	5.86 (11.0)	-0.79	2.86*	1.23
Afforestation	0.66 (3.9)	0.05 (0.5)	0.61	0.05	0.37
Land conservation	0.29 (2.8)	0.02 (0.2)	-0.04	0.00	0.01
Nursery/seedling production	0.14 (2.0)	0.00 (0.0)	0.14	0.00	0.08
Road construction/maintenance	0.63 (3.7)	0.65 (3.7)	-1.76**	-0.27	-0.96**
Other activities	2.96 (7.1)	3.44 (7.5)	0.45	1.98*	1.22*
Skills vector: individual SWC measures on private land					
Number of SWC measures	1.50 (1.0)	1.40 (0.9)	0.14	0.33**	0.25**
Days worked on SWC, last 12 months	9.00 (12.3)	8.08 (10.7)	1.54	2.29	2.04*
Household has [...] on its private land					
Any SWC measures	0.83	0.83	0.02	0.12*	0.08*
Grass strips/barriers	0.36	0.30	0.11	0.11	0.12**
Drainage/ditches/swales	0.06	0.10	0.00	0.07*	0.03
Trees as SWC measure	0.11	0.07	0.07*	0.05	0.07**
Contour bunds	0.33	0.31	-0.15*	0.02	-0.06
Marker ridges	0.25	0.24	0.02	0.01	0.02
Box ridges	0.31	0.30	0.08	0.06	0.07
Manure used, last agric. season	0.57	0.46	0.28**	0.18**	0.24**
Control variables					
Household size	5.73 (2.2)	5.29 (2.3)	-0.87**	-0.28	-0.51**
Maximum education level of head/spouse					
Primary completed	0.41	0.30	-0.06	-0.09	-0.07
Secondary completed or more	0.09	0.04	0.03	-0.01	0.01
Age of household head (in years)	43.51 (14.8)	41.65 (15.6)	-2.19	0.68	-0.48
Head/spouse with disability/chronic illness	0.08	0.12	0.01	0.03	0.02
Married household head	0.89	0.78	0.00	0.01	0.02
Number of months with insufficient food, last 12 months	3.88 (3.0)	3.64 (2.7)	1.40**	1.15**	1.29**
Number of 7 productive assets owned	1.15 (1.1)	0.94 (1.0)	0.48**	0.20	0.35**
Number of 14 domestic assets owned	4.03 (2.2)	3.43 (2.1)	0.36	-0.35	0.04
Business or wage employment	0.31	0.29	0.10	-0.03	0.03

Notes: Columns 1 and 2 display the mean in the control catchments, with the standard deviation (sd) below in parentheses for non-binary variables. Difference in means indicate the difference between control catchments and the treatment catchment (C-T), respectively for Always-MASAF-4 households (PW), Never-PW households (Non-PW), and both combined (Both). Productive assets are bicycle, motorcycle, car, phone, solar panel, brewing drum, and genset. Domestic assets are mortar, watch, bed, mattress, radio, sleeping mat, TV, table, improved stove, chair, kerosine stove, blanket, gas/electric stove, and cabinet. Asterisks indicate significance levels of differences in means based on t-tests: * for p<.05 and ** for p<.01

3.3.5 Econometric specifications

In this section, I formally describe the econometric specifications for implementing my empirical approach. For a given dependent variable y the estimated equation is the following:

$$(1) y_{hc,t} = \beta_{End} End_t + \beta_{Treat} Treat_c + \beta_{DiD} End_t \times Treat_c + \beta_{Cov} X'_{hc,t} + \varepsilon_{hc,t},$$

where $y_{hc,t}$ denotes the outcome for household h in catchment c and time t (where $t = 0$ is the baseline and $t = 1$ is the endline). End_t is a binary variable equal to 1 when $t = 1$. $Treat_c$ is equal to 1 when the household is considered as treated, and equal to 0 otherwise. In the ITT framework, a household is considered treated if it lives in the treatment catchment. The main coefficient of interest is β_{DiD} , representing the DiD effect of the enhanced model in comparison to the standard model. Equation (1) is estimated separately for each dependent variable described in Table 3.2. The vector $X'_{hcd,t}$ includes the household-level covariates listed in Table 3.2.

Note that Equation (1) does not include a dummy to account for the PW status of the household. Instead, it is estimated separately for the subsample of PW households and for the subsample of non-PW households. In the first case, PW households in the treatment catchment are compared to PW households in the control catchments. In the second case, non-PW households in the treatment catchment are compared to non-PW households in the control catchments. In addition, Equation (1) is estimated for the combined sample of PW households and non-PW households. This specification, thus, does not account for potential heterogeneity by PW status. Equation (1) is estimated with the ordinary least square (OLS) method that uses between-household and within-household variation. As robustness checks, I estimate it with the more restrictive panel fixed effects (FE) model that uses only within-household variation and estimate triple-difference (DDD) effects (based on the combined sample) as an alternative to the split samples by PW status.³⁷

To identify the TOT effect through the IV approach, I estimate the model depicted in Equation (1) using two-stage least squares (2SLS). My indicator for $Treat_c$ is in this case a dummy that is equal to 1 if someone from the household participated in at least one of the enhanced capacity building activities. This indicator is instrumented by the treatment catchment dummy. A good

³⁷ The results for the FE model and the DDD specifications are reported in Appendix 3.G: Asset vector: additional estimation results for the asset vector and in Appendix 3.H: Skills vector: additional estimation results for the skills vector.

instrument must be a strong predictor of the potentially endogenous variable (i.e., be relevant) and have no direct effect on the dependent variables and be uncorrelated with the omitted variables (i.e., be exogenous). Living in the treatment catchment is a strong predictor for participation in enhanced capacity building (as I show in section 3.4.1). Regarding exogeneity, I make the (albeit strong) assumption that the instrument is exogenous to the dependent variables of the asset vector because the tests in Section 3.3.4 show good baseline balance for the dependent variables and the control catchments were chosen specifically based on their similarities with the treatment catchment. However, the IV estimates for the dependent variables of the skills vector must be treated with caution due to the non-negligible differences revealed by the balance tests and by the fact that the argument is only based on observables. Hence, given these shortcomings, I prefer the ITT specifications because they yield conservative lower bound estimates, but I report the IV specifications additionally as upper bound estimates.

The characteristics of my data and identification strategy require a cautious approach to calculating standard errors. I need a method that is suitable for a DiD scenario where the sample comprises only of one treated cluster and three untreated clusters and where the number of observations per cluster varies considerably. The econometric literature suggests that there is no clearly preferable method for such a setup. The standard errors might be biased, irrespective of the method used. The default approach is to cluster standard errors at the level where the treatment was administered (Abadie et al., 2017; C. Cameron & Miller, 2014; MacKinnon & Webb, 2020). This would imply clustering at the catchment level. Yet, the conventional cluster-robust variance matrix estimator (that is used when specifying the cluster option in most STATA regression commands) is unreliable for DiD estimations with few (treated) clusters (Conley & Taber, 2011; Roodman et al., 2019). Bootstrap-based approaches, such as wild cluster bootstrap, are typically preferable in settings with few clusters, unbalanced clusters, or few untreated clusters (Roodman et al., 2019). However, in my setting where all three of these characteristics coincide, bootstrap-based approaches do not necessarily perform better (MacKinnon & Webb, 2018; Roodman et al., 2019). Given that there appears to be no method that is certain to deliver unbiased approximations, I show how results vary for different methods. In the main estimation tables, I report both un-clustered heteroskedasticity-robust standard errors and robust standard errors clustered at the catchment level. Results of ordinary

wild bootstrap (unrestricted and restricted) and wild cluster bootstrap (unrestricted and restricted) are available upon request.

Another limitation that follows from my setting is that I cannot make credible power calculations. I outlined the size of my sample and of relevant subgroups, by PW status and location, in Section 3.3.3. Considering these sample sizes and notwithstanding the challenge of calculating reliable standard errors, I argue that I have enough observations to regard the direction of effects as reliable and to also consider the magnitudes of the effects cautiously. When interpreting results, I focus at least as much on the economic significance of coefficients as on their statistical significance. These limitations also reduce the added value of other conventional robustness checks, such as multiple hypothesis testing.

3.4 Results

3.4.1 Uptake of the enhanced capacity building activities

Table 3.3 summarises the uptake of the enhanced capacity building activities, for all respondents in the treatment catchment whose PW status did not change between baseline and endline (i.e., the non-switchers) and separately for non-PW households and PW households. In short, awareness of the enhanced model and participation at the extensive margin are high, even for non-PW households. However, participation levels at the intensive margin are modest and patchy, even of most PW households. This ‘funnel of attrition’ in the intensity of participation in community projects is common (H. White et al., 2018).

Respondents were asked in the endline survey about their participation in eleven specific types of enhanced capacity building activities. Overall, 62% participated in at least one of them and even of the non-PW households almost half did so. At the intensive margin, households participated, on average, in 3.6 of the eleven types of activities, ranging from 2.8 activities for non-PW households to 4.2 activities for PW households. Put differently, 35% of households participated in at least three activities, 21% in at least five activities, 11% in at least seven activities, and very few in nine or more activities.

The high participation levels in the enhanced capacity building at the extensive margin for both PW households and non-PW households have two main implications. First, they make it *a priori* plausible that changes over time in outcomes of interest can be attributed to the enhanced

model. Second, they support the argument made in Section 3.3.5 that the indicator whether a household resides in the treatment catchment is a strong predictor of participation at the extensive margin and, therefore, a relevant instrument for the IV approach. However, due to the large difference of 33 pp between non-PW households and PW households in participation at the extensive margin, the instrument may be weaker for the former group than for the latter.

Table 3.3: Awareness of enhanced model and participation in enhanced capacity building activities

	Both (1)	Non-PW (2)	PW (3)
Aware of enhanced model	0.85	0.79	0.92
Participation in enhanced capacity building			
Extensive margin: participated in at least one activity	0.62	0.47	0.80
Intensive margin: number of activities attended, if >0	3.61	2.79	4.17
Participated in at least [...] of the activities			
3/11	0.35	0.20	0.53
5/11	0.21	0.09	0.34
7/11	0.11	0.05	0.17
9/11	0.04	0.02	0.06
11/11	0.01	0.01	0.00
Observations	189	101	88

Note: Column 1 shows figures for all non-switchers from the treatment catchment, meaning the Never-PW households and Always-MASAF-4 households from there. Columns 2 and 3 show the disaggregated figures for these two subgroups. In chronological order of implementation, these are the eleven categories of enhanced capacity building activities: first community meeting in 12/2016; VLAP validation in 3/2017; MCC establishment in 3/2017; raising awareness of communal watershed management through videos from Ethiopia in 4/2017; other large-scale awareness raising session in 2017; other small-scale awareness raising session in 2017; orientation on bylaw development in 6/2017; awareness raising regarding COMSIP in 6/2017; bylaw validation in 9/2017; bylaw signing in 1/2018; training on income generating activities in mid-2018. Figures for participation disaggregated by specific activities are presented in Appendix 3.C: Participation in the enhanced capacity building activities, details.

3.4.2 Asset vector: voluntary community work

The main DiD results for watershed management-related voluntary community work, which I interpret as an indicator of strengthening climate resilience through the asset vector, are presented in Table 3.4. I report four outcomes: workdays in three specific sectors (*afforestation*, *land conservation*, and *nursery*) and aggregated across *all sectors*. The latter includes also sectors unrelated to watershed management, such as roads and school-related construction, and serves as a gauge for the net effect of the enhanced model on overall community work.³⁸ Panel 1 shows results for the subsample of PW households, Panel 2 for non-PW households, and Panel 3 for PW and non-PW households combined. I report the ITT and IV estimates, both based on the OLS method.

³⁸ Estimation results for non-watershed management-related sectors are reported in Table G.3.17 of Appendix 3.G: Asset vector: additional estimation results.

Table 3.4: Voluntary labour contributions, main DiD results

	All sectors		Afforestation		Land conservation		Nursery	
	ITT	IV	ITT	IV	ITT	IV	ITT	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1: PW	20.41 (3.49)*** (1.15)***	25.78 (4.52)*** (1.25)***	5.21 (1.22)*** (0.13)***	6.56 (1.54)*** (0.13)***	10.68 (1.65)*** (0.28)***	13.48 (2.19)*** (0.30)***	4.07 (1.23)*** (0.68)***	5.13 (1.55)*** (0.74)***
Mean at baseline								
(treatment)		7.26		0.05		0.33		0.00
(control)		6.47		0.66		0.29		0.14
Panel 2: Non-PW	7.06 (2.40)*** (2.26)*	15.00 (5.12)*** (4.15)***	4.38 (1.05)*** (0.20)***	9.40 (2.35)*** (0.36)***	6.95 (1.31)*** (0.30)***	14.94 (2.99)*** (0.61)***	2.49 (0.82)*** (0.13)***	5.36 (1.79)*** (0.22)***
Mean at baseline								
(treatment)		3.00		0.00		0.02		0.00
(control)		5.86		0.05		0.02		0.00
Panel 3: Both	13.25 (2.17)*** (1.74)***	21.37 (3.47)*** (2.40)***	4.76 (0.81)*** (0.14)***	7.67 (1.32)*** (0.19)***	8.71 (1.04)*** (0.24)***	14.06 (1.77)*** (0.34)***	3.12 (0.75)*** (0.34)***	5.03 (1.21)*** (0.48)***
Mean at baseline								
(treatment)		4.97		0.02		0.16		0.00
(control)		6.20		0.39		0.17		0.08
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$; Standard errors are reported in parentheses below the DiD coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The unit of the dependent variables are the number of workdays in the respective sector during the last 12 months. To mitigate distortion by outliers, values were winsorised at fraction 0.98. The underlying sample includes observations from the special village. Additional estimation results are reported in Appendix 3.G: Asset vector: additional estimation results, including for the non-watershed management-related sectors (roads and other, especially school-related construction) in Table G.3.17. The outcome *all sectors* also comprises workdays in these sectors.

Across all reported samples, specifications, and outcomes, the DiD estimates show substantial and statistically significant increases in voluntary community workdays in the treatment catchment compared to the control catchments. For PW households (Panel 1), there is an average difference of at least 20 workdays for the aggregated total across all sectors, 5 workdays in afforestation, 10 workdays in land conservation, and 4 workdays in nursery activities.³⁹ The IV estimates are approximately 25% larger than the corresponding ITT estimates for all four outcomes. Turning to the ITT results for non-PW households (Panel 2), the differences compared to non-PW households in the control catchments are 6 workdays for the aggregated total, 4 workdays in afforestation, 7 workdays in land conservation, and 2 workdays in nursery activities. The corresponding IV estimates are more than twice as large, suggesting that within the treatment catchment there is a large difference in contribution to

³⁹ I use the ITT point estimates based on the FE model as the lower bound for the effect sizes.

community work between non-PW households that participated in enhanced capacity building and non-PW households that did not participate. Across all groups, the largest sectoral effects are observed for land conservation, followed by afforestation, and then nursery activities. This is consistent with the relative labour intensity of these sectors.

The evidence presented thus far suggests that the enhanced model substantially increased the quantity of voluntary community work in sectors relevant for climate resilience compared to the control catchments where the standard model was implemented. The results further show that the enhanced model has a large positive net effect on the total volume of voluntary community work. The fact that the effect sizes of the three watershed management-related sectors approximately add up to the net effect rules out major crowding effects. The estimation results for roads and other (mainly school-related) construction activities in Table G.3.17 of Appendix 3.G: Asset vector: additional estimation results further substantiate this interpretation. The absence of this form of crowding out is consistent with evidence from a payment for ecosystem service (PES) programme in Mexico that has critical similarities to PWPs (Alix-Garcia et al., 2019).⁴⁰ Employing a randomised controlled trial, the authors show that the increase in conservation activities related to the PES did not come at the expense of reductions in conservation activities by participants elsewhere.

My result that PW households increased their contributions to watershed management-related community work is consistent with studies of other social protection programmes that find an increase in pro-social attitudes or behaviour of programme beneficiaries (Adato, 2000; Attanasio et al., 2015; Evans et al., 2019; Loewe et al., 2020). While effect sizes cannot be directly compared, for example because none of these studies look at watershed management-related cooperation, my effects appear to be quite pronounced.

My result that non-PW households also substantially increased their contributions to watershed management-related community work stands, at first glance, in contrast to what other studies find. For example, a qualitative study of the effect of Mexico's conditional cash transfer programme PROGRESA on community relationships finds that many non-recipients no longer want to participate in voluntary community work because they felt that this should henceforth

⁴⁰ At the centre of most PES programmes are contracts between institutions and individual landowners. The institution pays the landowner for rendering ecosystem services on their private land. However, in some PES programmes, including the one studied by Alix-Garcia et al. (2019), contracts are also signed with groups who jointly manage land. Especially PES programmes with this feature offer lessons that are relevant for PWPs with environmental objectives (such as the two PW models studied in this paper).

be done only by the cash recipients (Adato, 2000). Moreover, there is a growing body of evidence that financial incentives can crowd out intrinsic motives to preserve natural resources, under conditions that are not yet entirely understood (Agrawal et al., 2015; Neuteleers & Engelen, 2015; Popa, 2015; Rode et al., 2015).

This raises the question why the effects for both PW households and especially non-PW households are at the upper end or even above of what one might have expected based on the literature. Complementary qualitative research suggests that the high participation in community works can be explained by an interplay of (1) effective awareness raising as to how watershed management can bring communal and individual benefits, (2) strong leadership by the traditional leaders who, in cooperation with the micro-catchment committees, effectively mobilised people, and (3) a stick and carrot approach that linked PW participation and community work participation. The last aspect refers to the practice that participation in the watershed management-related community works increased chances for non-PW households to become enrolled if spots became available (*carrot*) and non-participation in community works without a proper reason could, as a last resort, be sanctioned with exclusion (*stick*). Similar stick and carrot approaches also apply in the control catchments but not to watershed management-related community work (if such community work is undertaken at all). A more in-depth analysis of the motives for participation is provided in a qualitative study by Beierl and Grimm (2018).

The findings reported in this section withstand a battery of robustness checks. Results for DDD instead of split samples by PW status and FE model instead of OLS are reported in Appendix 3.G: Asset vector: additional estimation results, while the following checks are available upon request: truncating and winsorising the dependent variables at different levels; using dummy variables as dependent variables instead; using Poisson regression instead of OLS; excluding the special village; excluding only the entrants to the MASAF-4 PWP instead of also the entrants to IFA; and varying the way standard errors are calculated (clustering, bootstrapping, and combinations thereof etc.).

3.4.3 Skills vector: adoption of SWC measures on private land

Table 3.5 and Table 3.6 show the main DiD results for the adoption of SWC measures on private land which I interpret as an indicator of strengthening climate resilience through the skills vector. The dependent variables in Table 3.5 are *number of different types of SWC measures on private land*, the *number of SWC-related workdays spent by household on its*

private land in the last twelve months, and a dummy whether the household has any SWC on its private land. The dependent variables in Table 3.6 are dummies denoting respectively whether the household has *drainage* or *box ridges* on its private land, and whether the household applied *manure in the past twelve months*.⁴¹ In both tables, Panel 1 shows the DiD results for the subsample of PW households, Panel 2 for non-PW households, and Panel 3 for the combined sample.

Table 3.5: SWC adoption, main DiD results for aggregate outcomes

	Number of SWC measures		Number of SWC workdays		Any SWC measure	
	ITT (1)	IV (2)	ITT (3)	IV (4)	ITT (5)	IV (6)
Panel 1: PW	0.062 (0.186) (0.047)	0.078 (0.232) (0.049)	1.831 (1.932) (1.017)	2.289 (2.389) (1.095)**	-0.004 (0.063) (0.036)	-0.005 (0.078) (0.039)
Mean at baseline (treatment)		1.36		7.46		0.81
(control)		1.50		9.00		0.83
Panel 2: Non-PW	0.150 (0.176) (0.015)***	0.312 (0.389) (0.031)***	2.600 (1.393)* (0.932)*	5.513 (3.014)* (1.675)***	0.066 (0.070) (0.023)*	0.136 (0.154) (0.040)***
Mean at baseline (treatment)		1.07		5.79		0.71
(control)		1.40		8.08		0.83
Panel 3: Both	0.100 (0.128) (0.026)**	0.161 (0.208) (0.035)***	2.181 (1.166)* (0.947)	3.510 (1.874)* (1.309)***	0.030 (0.047) (0.029)	0.047 (0.077) (0.040)
Mean at baseline (treatment)		1.20		6.57		0.75
(control)		1.45		8.61		0.83
Controls	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The dependent variables *number of SWC measures* and *any SWC measure* was modified based on the assumption that SWC measures that were there reported at baseline are still there at endline even if it was not reported. The underlying sample includes observations from the special village. Households that either did not farm at baseline or endline are disregarded. Additional estimation results are reported in Appendix 3.H: Skills vector: additional estimation results.

The DiD estimates in Table 3.5 show a small increase for the two non-binary outcomes in the treatment catchment compared to the control catchments. The disaggregation by PW status suggests that this effect is primarily driven by non-PW households (Panel 2). Based on the ITT

⁴¹ Estimation results for additional outcomes are reported in Table H.3.20 of Appendix 3.H: Skills vector: additional estimation results.

estimates, non-PW households increased the number of SWC measures by 0.15 types and the number of workdays by 2.3 days, compared to non-PW households in the control catchments. Effects for PW households for the non-binary outcomes are also positive but smaller and not significant (Panel 1). The share of non-PW households with *any SWC measures* increased by at least 6 pp compared to non-PW households in the control catchments (Panel 2). By contrast, there is no change at all for PW households (Panel 1). To put the positive results into perspective, it is important to recall that they coincide with lower baseline levels in the treatment catchment compared to the control catchments. At endline, the gaps narrowed but levels still remain somewhat lower in the treatment catchment. For all outcomes, the size of the standard errors varies considerably, depending on whether I cluster them or not, which reaffirms the need to be cautious regarding the accuracy of standard errors in my setting.

Table 3.6: SWC adoption, main DiD results for specific SWC measures

	Drainage		Box ridges		Manure	
	ITT (1)	IV (2)	ITT (3)	IV (4)	ITT (5)	IV (6)
Panel 1: PW	0.000 (0.051) (0.012)	0.000 (0.063) (0.013)	0.004 (0.080) (0.030)	0.004 (0.100) (0.032)	0.141 (0.084)* (0.040)**	0.175 (0.109) (0.044)***
Mean at baseline (treatment) (control)		0.06 0.06		0.23 0.31		0.29 0.57
Panel 2: Non-PW	0.071 (0.055) (0.013)**	0.152 (0.118) (0.027)***	0.047 (0.081) (0.009)**	0.098 (0.174) (0.019)***	0.012 (0.085) (0.052)	0.018 (0.187) (0.093)
Mean at baseline (treatment) (control)		0.03 0.10		0.24 0.30		0.28 0.46
Panel 3: Both	0.037 (0.037) (0.009)**	0.059 (0.059) (0.013)***	0.027 (0.056) (0.011)*	0.043 (0.091) (0.016)***	0.070 (0.060) (0.032)	0.113 (0.101) (0.045)**
Mean at baseline (treatment) (control)		0.05 0.08		0.24 0.31		0.28 0.52
Controls	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The dependent variables *drainage* and *box ridges* are modified based on the assumption that SWC measures that were there reported at baseline are still there at endline even if it was not reported. The underlying sample includes observations from the special village. Households that either did not farm at baseline or endline are disregarded. Additional estimation results are reported in Appendix 3.H: Skills vector: additional estimation results.

Table 3.6 offers insights which specific SWC measures drive the changes in aggregate outcomes observed in Table 3.5. Results suggest that the observed increases for non-PW households can be primarily attributed to the adoption of drainages (+7 pp) and box ridges (+5 pp). For PW households in the treatment catchment, there are no indications of robust statistically significant differences to the control catchments for drainage or box ridges. Regarding grass barriers, marker ridges, and contour bunds, there are no robust differences for PW households or non-PW households (see Table H.3.20 in Appendix 3.H: Skills vector: additional estimation results). While some coefficients are statistically significant, their size does not exceed 3 pp. Therefore, I do not consider these results as economically significant.

I discuss the use of manure separately from the other SWC outcomes because in the enhanced model its adoption by households on private land was actively promoted through demonstration sessions, unlike the other SWC measures where the skills transfer took mainly place on-the-job (i.e., during PW or community works).⁴² During the intervention period, the share of PW households in the treatment catchment that used manure strongly increased compared to their counterparts in the control catchments (+14 pp). This considerably narrowed the gap in the use of manure that existed at baseline, but levels remain still below those in the control catchments. For non-PW households, no differences are detected. These results are consistent with the observation that participation in enhanced capacity building measures, including manure-related activities, was higher among PW households than non-PW households (shown in Section 3.4.1).

Overall, the key difference between the enhanced model and the standard model in terms of the skills vector seems to be that skills transfer extends to non-PW households. It is not clear how to interpret or explain the limited effects observed for PW households of the treatment catchment (except regarding manure). One possible explanation could be that increases for PW households coincided with simultaneous increases for PW households in the control catchments.⁴³ Another explanation could be that adoption by PW households already took place across all catchments during the first year of the MASAF-4 PWP, i.e., before the baseline

⁴² Moreover, it is not only a SWC measure but also a potent organic fertiliser and, therefore, has a more direct productive effect. It is also a potential complement to or substitute for chemical fertiliser. In principle, I could investigate the relationship between fertiliser use and manure use because I collected information on fertiliser use. However, it would go beyond the scope of this paper.

⁴³ A strong positive interaction of PW and time ($PW * End$) in DDD specifications would support this explanation. However, while these coefficients are indeed mostly positive, they are small and rarely statistically significant (see Table H.3.19 in Appendix 3.H: Skills vector: additional estimation results).

survey and the start of the enhanced model. In support of this explanation, baseline SWC adoption levels of PW households were above those of non-PW households for most outcomes, both in the treatment catchment and the control catchments. However, it could also be that these differences already existed prior to the start of the MASAF-4 PWP.

Moreover, as noted in Section 3.3.4, it could be that some of the observed changes in SWC adoption are the outcome of PW or communal work that took place on private land rather than the outcome of the owners' individual efforts. Table 3.7 shows the number of new adoptions (Columns 1 and 2), the share of those that coincide with PW or community work on that land (Columns 3 and 4), and the difference in shares between the treatment catchment and control catchments (Column 5).

Table 3.7: New adoption coinciding with PW or community work on land (between baseline and endline)

	Number of new adoptions		Share of adoptions coinciding with PW/CW on land		Difference (5)
	Treatment (1)	Control (2)	Treatment (3)	Control (4)	
Number of SWC measures	135	221	0.27	0.28	-0.01
Any SWC measure	27	43	0.26	0.44	-0.18
Drainage	24	26	0.29	0.23	0.06
Grass strips/barriers	53	104	0.36	0.38	-0.02
Contour bunds	35	63	0.29	0.27	0.02
Marker ridges	9	20	0.33	0.05	0.28
Box ridges	18	18	0.17	0.22	-0.06
Manure	73	118	0.26	0.31	-0.05

Notes: CW denotes community work. *Difference* reflects the differences in shares (Column 3 minus Column 4).

The overlap of new adoptions with PW or community work for most SWC categories is higher in the control catchments, including for number of *SWC measures*, *any SWC measure*, *box ridges*, and *manure*.⁴⁴ For drainage, the overlap in the treatment catchment is 6 pp bigger than in the control catchments. Assuming that drainage was among the assets created during the PW or community work in these cases (which I cannot verify based on my data), this could diminish the increase in adoption of drainage that can be attributed to owners' individual work. As additional validation, I therefore check how the regression results change if I make either of the following two modifications. First, I additionally control for whether PW or community work took place on the household's land. Second, I restrict the sample to cases where no PW or community work took place on the household's land between baseline and endline. The

⁴⁴ Overlap is substantially higher in the treatment for marker ridges although this difference of 28 pp must not be overinterpreted considering that the 33% overlap in the treatment catchment is based on merely nine new adoptions.

previously observed increase in drainage is robust to these modifications.⁴⁵ Hence, the data on the overlap overall corroborate the claim that the observed differences in adoption are primarily driven by owners' individual work.

In Appendix 3.I: Checking robustness to issues concerning the data on SWC adoption, I further show that the results are robust to two potential problems concerning the data (collection) on SWC measures. In terms of direction and economic significance of the point estimates, the findings reported in this section also withstand robustness checks. Results for DDD instead of split samples by PW status and FE model instead of OLS are reported in Appendix 3.H: Skills vector: additional estimation results. Upon request additional checks are available where the special village is excluded or where only entrants to the MASAF-4 PWP are excluded but not IFA entrants. In terms of statistical significance, the robustness of the results is difficult to assess. Varying the way standard errors are calculated (clustering, bootstrapping, and combinations thereof etc.) leads to widely different confidence intervals, yet it is not clear from the literature how reliable standard errors can be computed in my setting.

To sum up, my findings suggest that the enhanced model increased the contribution to climate resilience compared to the standard model by fostering the private adoption of some climate-smart practices. The result that the presence of PWPs is associated with an increase in private adoption of such practices is consistent with the literature (Gebremedhin & Swinton, 2003; Hagos & Holden, 2006; Ignaciuk et al., 2021). Hagos and Holden (2006) find this for a setting with communal conservation programmes, consisting of both unpaid community work (mass mobilisations) and PW (food-for-work) in rural Ethiopia. Ignaciuk et al. (2021) find such evidence for the regular MASAF PWP in Malawi based on an analysis of the Integrated Household Survey Panel (IHPS). My findings suggest that this effect can be leveraged to non-PW participants with the design changes of the enhanced model.

Gebremedhin and Swinton (2003) identify two mechanisms, also regarding pre-PSNP rural Ethiopia. First, they find that PW can provide learning opportunities that result in long-term investments, for example in stone terraces, if land tenure is secure, labour available, and farms are nearby. Without PW and secure land tenure, short-term investments, for example in soil bunds (contour bunds), are more common. In my setting, the conditions for long-term investments are met, but so far only investments in short-term measures increased. In principle,

⁴⁵ These additional regression results are available upon request.

long-term investments could still follow. However, it is unlikely because the implementers of the enhanced model did not see the need for more than what was already collectively constructed in that location.⁴⁶ In that sense, once one accounts for differences in the context, my findings seem consistent with this mechanism. Second, they find that PW which takes place on private land is associated with lower individual short-term and long-term investment. By contrast, I find an increase in private investments despite public activities on private land in the area. This discrepancy could be due to differences in the scale of private activities or in expectations of whether an activity would eventually be done through public activities. However, I cannot test this with my data.

3.4.4 Possible mediating factors and threats to the validity of inference

As noted, the identification strategy relies critically on the parallel trends assumption. With only one data point per household from the pre-intervention period, I can test whether prior levels were comparable, as I have done in Section 3.3.4, and control for relevant baseline differences in my econometric specifications, as I also do, but I cannot test for parallel trends. Moreover, I cannot control for catchment-level differences in my econometric analysis because there are only one treatment catchment and four catchments overall. In this section, I discuss some potential mediating factors as well as possible reasons why the parallel trends assumption may not hold along with evidence that would suggest that these are not a serious concern.

Role of extra tools and tree seedlings provided through the enhanced model

As noted in Section 3.2.3, implementers of the enhanced model responded to the lack of inputs provided through MASAF-4 in 2017 by giving out extra tree seedlings and a limited number of basic tools, especially some wheelbarrows, to the communities in the treatment catchment. The tree seedlings prevented an impending slowdown of collective nursery and afforestation activities (i.e., both PW and community work). These extra seedlings may have somewhat increased the magnitude of differences between the treatment catchment and the control catchments, especially regarding nursery and afforestation activities. However, I consider it unlikely to fully explain the large differences in levels of voluntary community work at both the extensive and intensive margin. According to the implementers, the extra tools played a

⁴⁶ This is also why I do not use terraces as a dependent variable in my analysis.

negligible role in watershed management-related community work and private adoption of SWC measures. I have no information to validate this.

Differences in PWP coverage

The visibility of the MASAF-4 PWP in a catchment could increase the likelihood of spillover effects of the programme to non-participants independent of differences in programme content, especially in terms of skills transfers. I use the coverage rate of the MASAF-4 PWP as a proxy for how intensely a catchment was exposed to the PW activities. Coverage refers to the fixed number of spots available on the MASAF-4 PWP relative to the total number of households living in that catchment. Note that coverage remained constant during the study period and was therefore not modified in the enhanced model.⁴⁷ In two of the three control catchments coverage is close to the 47% in the treatment catchment (43% and 42%, respectively). In one control catchment, only 28% were covered, but the rate would effectively be more similar to the other catchments if it were calculated in reference to the population of the communities where the PW activities were concentrated and where the majority of the PW participants reside.⁴⁸

Differences in exposure to shocks and access to support

Substantial differences in exposure to shocks or in access to programmes or support (unrelated to the PW) which arose during the intervention period could threaten the parallel trends assumption. Differences in levels (i.e., differences that already existed at baseline and persisted at endline) are less problematic unless they differentially constrain or enable changes in my outcomes of interest. In particular, as noted earlier, people in acute distress or with reduced labour capacity are probably less likely to partake in community works or to implement new labour-intensive agricultural or SWC practices. Table J.3.22 in Appendix 3.J: Shocks, support, and extension services during intervention period displays information on shock exposure and access to social assistance, development programmes, and extension services during the intervention period (i.e., between baseline and endline). I use this along with the corresponding

⁴⁷ Changes in population size between baseline and endline are not accounted for, but there is no reason to believe that it changed substantially during these 24 months.

⁴⁸ Reliable information about the population size of this subset of the catchment was not available. However, for the reported coverage rate, I subtracted the 540 households living in the local trading centre because they had minimal exposure to the PWP and were therefore also not included in the survey sample. If they are not subtracted, the coverage rate is 22%.

pre-intervention information (Section 3.3.4) to discuss some pathways how differences regarding these factors might mediate or confound my empirical results.

Regarding shocks, the endline data further underscore the importance to control in my econometric analysis, as I do, for the food gap (i.e., an indicator of food insecurity), and for disability/chronic illness of the household head or spouse (i.e., an indicator of health and labour capacity). First, regarding food insecurity, it appears that there is a difference in levels rather than trends. Already at baseline, food insecurity had been more acute in the control catchments because they had been more severely affected by drought and the difference persisted at endline although the gap narrowed. Second, regarding health, more households in the treatment catchment reported to struggle with illness (+16 pp) at endline. This appears to be a difference in trends because at baseline there had been no difference between catchments.

I cannot rule out that the differences in the level of food insecurity and in health trends differentially affect my outcomes of interest given that my outcomes are both contingent on labour capacity and the absence of acute distress. Controlling for food insecurity and health status only partially addresses this concern. Yet, the higher support through social assistance that the control catchments received (-20 pp) somewhat alleviates the constraints imposed by higher food insecurity and, thus, improves comparability to the treatment catchment in this respect. In particular, control catchments received more support through the emergency food response (14 pp) and subsidised fertiliser programme (6 pp). These differences were already observed at baseline (see Section 3.3.4). I see no other channel through which social assistance would make labour contributions to community work or SWC adoption systematically more or less likely.

For the interpretation of my empirical results for the outcome *adoption of manure* it is relevant that more households in the treatment catchment report to struggle with the affordability of farm inputs, both at baseline and endline (around 10 pp in both survey waves). If it were a new trend, it could have offered an alternative explanation for the increase in the adoption of manure in the treatment catchment that would not be primarily driven by the enhanced model.⁴⁹ However, since it appears to be a persistent difference in levels, it does not weaken the attribution of the observed increase to the enhanced model. It also implies that households in

⁴⁹ Moreover, a closer look shows that for PW households there is no difference between the treatment catchment and control catchments. This is precisely the group for which I find the largest increase in the use of manure in Section 3.4.3.

the treatment catchment were probably receptive for the manure-related activities promoted through the enhanced model. For other shocks, I find no indications of relevant differences.

Other development projects with a focus on watershed management, environmental conservation, conservation agriculture etc. could be a serious threat to the parallel trends assumption, but there are no indications that any other project was implemented between baseline and endline.

The observed differences regarding agricultural extension services (AES) are consistent with the modifications that the enhanced model makes to the standard model in terms of skills transfer. People in the treatment catchment, irrespective of their PW status, were more likely to have received AES, specifically from friends (+13 pp), government extension workers (+10 pp), and other farmers (+4 pp). Especially PW households were more likely to receive AES from government extension workers than their counterparts in the control catchments (+20 pp). These patterns reflect the capacity building approach of the enhanced model whereby the government extension workers intensely interact with the micro-catchment committee members, most of whom are PW households. These were then expected to disseminate the knowledge to their fellow community members. In terms of topics, advice on natural resource management and, to a lesser extent, irrigation was more prevalent in the treatment catchment. These were indeed the two most prominent topics in the capacity building strategy of the enhanced model. For other topics, there is no difference.

3.5 Conclusion

The realisation that environmental shocks tend to disproportionately affect the poor and that climate change is expected to exacerbate this, have led to growing interest in understanding and enhancing the contribution of social protection programmes to strengthening climate resilience. The biggest potential is often ascribed to PWPs, provided they create ‘climate resilient’ infrastructure (asset vector) and transfer knowledge of adaptive practices (skills vector). Studies relating to large-scale programmes such as India’s MGNREGA and Ethiopia’s PSNP find some evidence that substantiate this claim (Fischer, 2019; Gebremedhin & Swinton, 2003; Godfrey-Wood & Flower, 2018), while others do not (Adam, 2015; Gazeaud & Stéphane, 2020). To date, it remains unclear what explains differences in outcomes. In particular, there is a lack of empirical evidence that directly investigates whether and which

design changes to make existing programmes climate-smarter succeed. This paper contributes such evidence from PW in Malawi. Using a difference-in-difference approach based on two-period panel data from Malawi, I analysed how a modified approach performs compared to the standard approach of Malawi's largest PWP over a period of 24 months. The main modifications to strengthen climate resilience are, first, that the work activities are embedded in a communal watershed management plan and attempt to not only rely on paid PW labour for its implementation but to also mobilise further voluntary labour contributions from the community and, second, a capacity building strategy is added to promote knowledge and the adoption of watershed management-related practices. Wage-related design features are not changed.

From starting levels of practically zero, the modified approach considerably increased the total volume of voluntary communal watershed management activities, specifically those related to land conservation, afforestation, and nursery activities. While the increase was mainly driven by PW participants, non-participants also made substantial contributions. The increases did not come at the expense of community work in other sectors. In fact, there is a large positive net effect on total community work. Moreover, a small increase in the adoption of soil and water conservation practices on private land is observed, especially for non-PW participants.

Overall, these findings imply that modest design changes in the approach to the work activities (asset vector) and capacity building (skills vector) can make PW climate-smarter by strengthening the adaptive capacity of vulnerable households. In particular, they can broaden the engagement in and adoption of climate-smart activities beyond the group of PW participants.

In terms of external validity, the findings of this paper may have some relevance in other environmental hotspots of countries where no integrated watershed management plans exist yet, where adoption levels of basic soil and water conservation practices are low, where the majority of people relies on household farming as their primary economic activity, and where a substantial part of the farming population has excess labour supply for most of the year.

Given the evaluation horizon of 24 months and the time it takes for watershed management activities to unfold their full impacts, this paper had to concentrate on intermediate short-term outcomes. Continued evaluation is needed to check whether the voluntary community work and the adoption of SWC measures are sustained and ultimately translate into tangible improvements in climate resilience (e.g., reduced soil erosion, better and more stable yields,

and higher income. Regarding the latter, other studies suggest that this cannot be taken for granted (Gazeaud & Stéphane, 2020; Hope, 2007). Regarding the continuation of community work, a qualitative study of another watershed programme in Malawi shows that work activities continued beyond the expiration of the PW support only in the one catchment where the locals had initiated watershed management themselves before the start of the PWP, whereas non-PW activities remained limited in the other catchments (Reichert, 2014).⁵⁰ This points to the importance of intrinsic motivation for sustainability. In the literature on payment for ecosystem services (PES), there is some quantitative evidence from Columbia that conservation behaviour persisted long after a planned cessation of payments in settings where programmes aimed to build up assets such as trees (Calle, 2020; Pagiola et al., 2016).⁵¹

Another related question for further research is how an enhanced model like the one evaluated in this paper compares to community-based watershed management projects that do not have a PW component (i.e., do not offer wage labour) in terms of community work, skills transfer, and sustainability. Large-scale studies that cover more catchments would also be helpful to build more confidence in the external validity of findings. Randomised controlled trials with a more clearly defined and controlled treatment could offer more insights into the role of specific design changes. It has also long been understood that the role of local institutions and actors must be studied in order to unpack how community-based interventions operate (Agrawal & Gibson, 1999). This aspect has been investigated in complementary qualitative research (Beierl & Grimm, 2018), but goes beyond the scope of this paper.

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⁵⁰ PW in that watershed programme took the form of food-for-works and was unrelated to the PWP evaluated in this paper.

⁵¹ By contrast, overuse of existing natural resources resumed in high pressure settings where PES programmes had aimed to restrict the use, irrespective of whether the payment cessation was planned (Jayachandran et al., 2018) or unplanned (Etchart et al., 2020).

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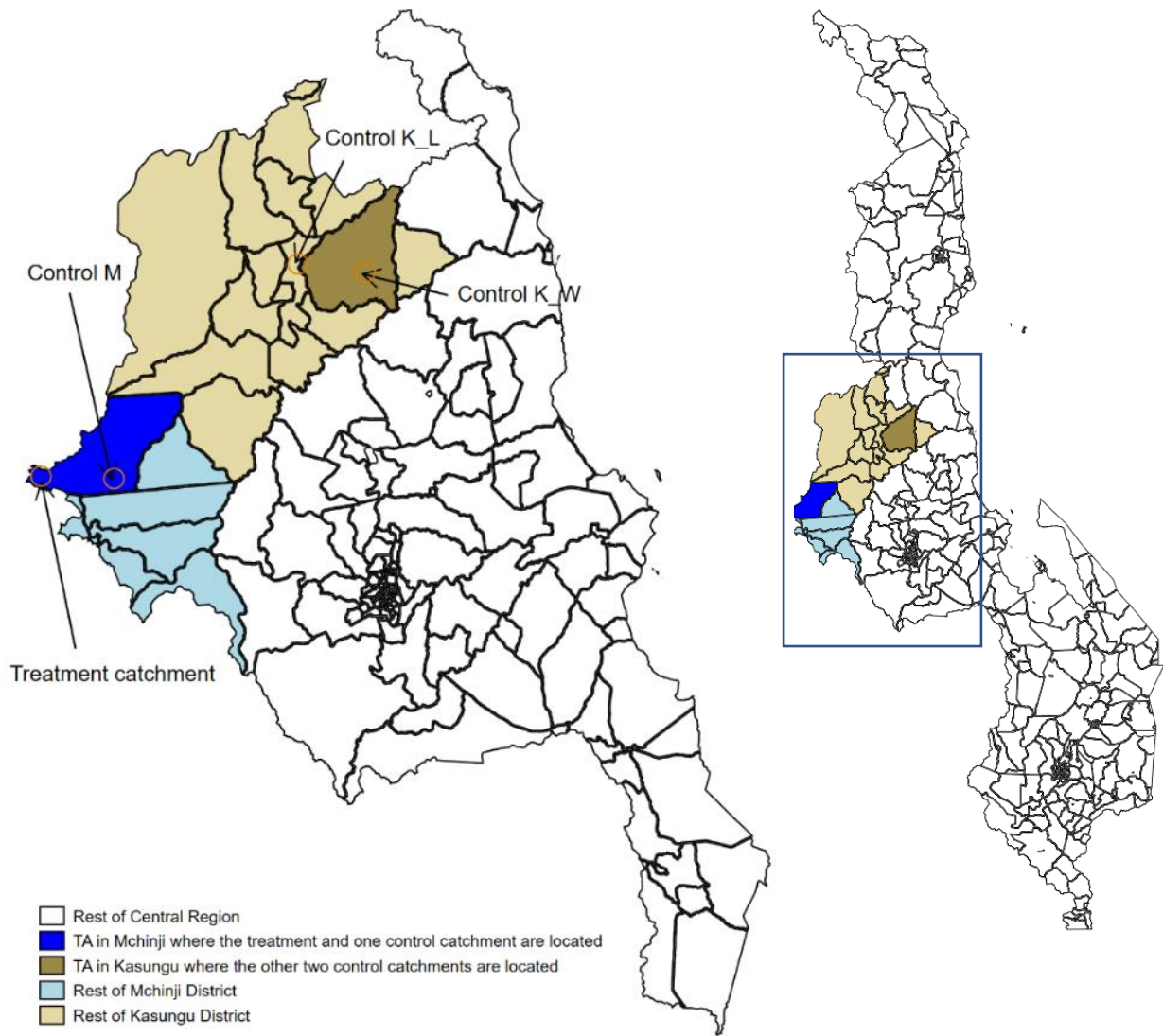
Appendix

Appendix 3.A: Survey locations and selection criteria

Given that the treatment catchment had been chosen early on by the implementers of the enhanced model, control catchments had to be found that were as similar to it as possible in terms of the outcomes of interest as well as the wider socio-economic and environmental situation and trends. The selection was supported by an international watershed management expert and guided by the following list of criteria: MASAF-4 PWP operating in the catchment⁵²; rugged undulated topography; high level of land degradation with visible signs of soil erosion (e.g., gullies); alarming rate of deforestation; mix of land uses that comprises forest as well as crop production with and without irrigation; same climate zone and reasonable expectation of similar weather patterns; subsistence maize farming as main livelihood activity of most people in the area, but many also generate some income from cash crops; wide-spread chronic poverty and seasonal food insecurity even in normal years; and remote location but nevertheless accessible by car during a normal rainy season. Figure A.3.1 shows the survey locations.

⁵² Using control catchments without the MASAF-4 PWP was not a viable option due to financial constraints and due to the pro-poor geographical targeting approach used by the MASAF-4 PWP (described in Section 3.2.2).

Figure A.3.1: Survey locations



Notes: TA = Traditional Authority (subunit of districts)

Appendix 3.B: Attrition test results

In addition to the attrition-related information reported in Section 3.3.2, Table 3.8 presents the sample size and attrition rate by catchment and PW status at baseline.

Table 3.8: Sample size and attrition rate, by catchment and baseline PW status

District	Catchment type (Code)	PW households	Non-PW households	Total households
Mchinji	Treatment	113/128 (12%)	157/180 (13%)	270/308 (12%)
	Control M	79/87 (9%)	76/90 (16%)	155/177 (12%)
Kasungu	Control K_W	79/83 (5%)	54/80 (33%)	133/163 (18%)
	Control K_L	109/134 (19%)	104/142 (27%)	213/276 (23%)
Total		380/432 (12%)	391/492 (21%)	771/924 (17%)

Note: The table shows the number of households re-interviewed at endline relative to the number of households interviewed at baseline. The corresponding attrition rates are in parentheses. For data confidentiality reasons, codes instead of names are used for the control catchments. PW status reflects whether a household was enrolled in the MASAF-4 PWP at baseline.

As noted, my empirical analysis uses the balanced sample, meaning baseline information from attrited households is not considered. This decision is primarily based on the reasons stated in Section 3.3.2. To further rule out attrition bias, I regress the binary attrition status on catchment dummies, the PW status at baseline, and various socio-economic and demographic variables. In addition, I run regressions where I interact the location dummies with the household PW status to allow the PW effect to vary by location.

The results in Table B.3.9 confirm the previously noted spatial pattern and positive association of PW status. Regarding socio-economic and demographic factors, I find the expected positive association between attrition and disability or chronic illness. Being married is negatively associated with attrition, probably because non-elderly unmarried people are more mobile than non-elderly married people. Other factors such as education, age, household size, and wealth proxies do not seem to play a role. In addition, I ran similar regressions to check whether any of the dependent variables are strongly correlated with attrition.⁵³ There are no statistically significant differences for any of the outcomes, except for voluntary community contributions to afforestation and, albeit weaker, to nursery activities. These exceptions are not surprising because one would only expect such contributions from those who plan to stay in the area and to, therefore, be around when the benefits of planted trees materialise eventually. To sum up, the findings of these additional attrition tests support the verdict from Section 3.3.2 that observable differences between attrited and non-attrited households are unlikely to bias the results when using the balanced panel.

⁵³ The regression tables for these tests are available upon request.

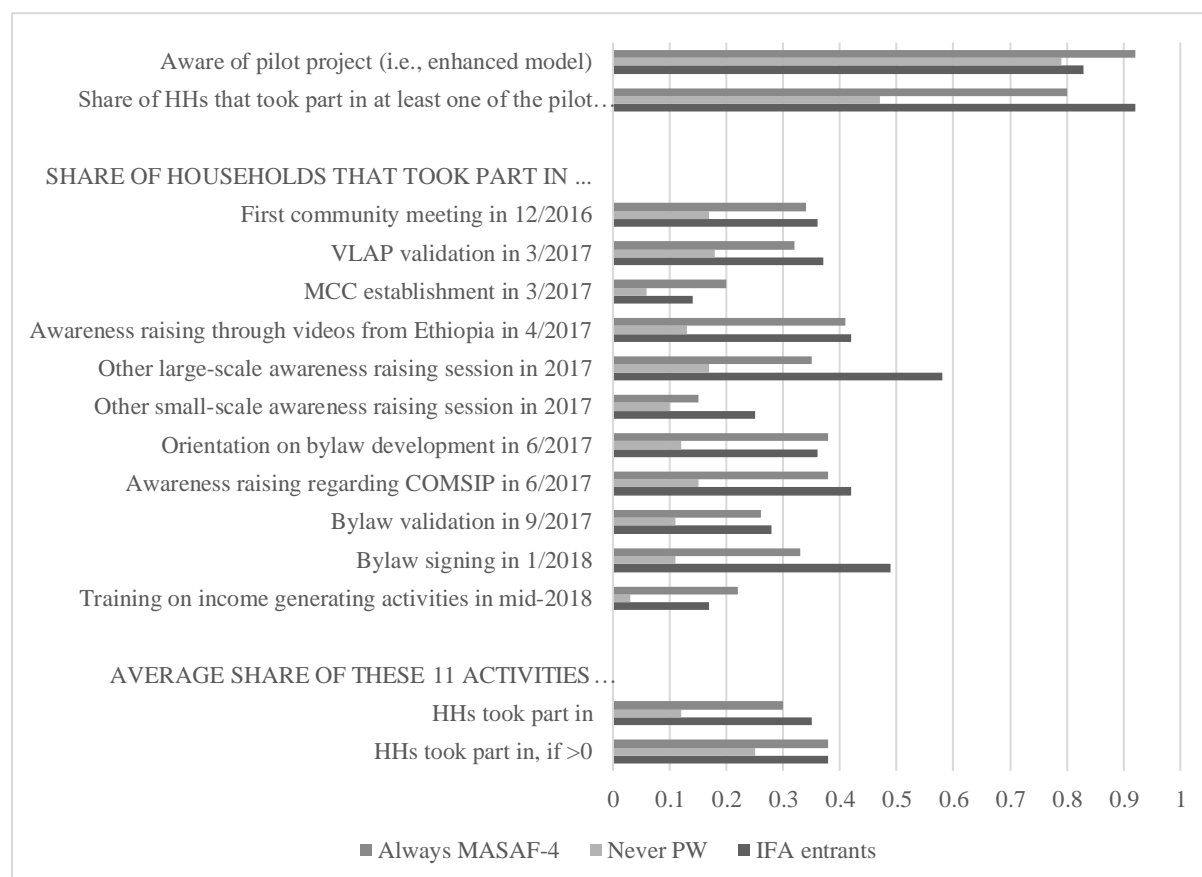
Table B.3.9: Attrition test

	(1)	(2)	(3)	(4)	(5)	(6)
In PWP at baseline (PW)	-0.083***	-0.125***		-0.066***	-0.069***	-0.137***
	(0.024)	(0.031)		(0.025)	(0.025)	(0.038)
Treatment catchment (Treat)		-0.122***			-0.087***	-0.152***
		(0.035)			(0.029)	(0.040)
Treat * PW		0.114**				0.153***
		(0.049)				(0.055)
Control_M					-0.093***	-0.138***
					(0.033)	(0.050)
Control_M * PW						0.096
						(0.064)
HH size			-0.002	-0.001	-0.001	-0.001
			(0.006)	(0.006)	(0.006)	(0.006)
Maximum years of education completed by head/spouse			0.004	0.005	0.005	0.005
			(0.005)	(0.005)	(0.005)	(0.005)
Age of household head (in years)			-0.005	-0.004	-0.004	-0.004
			(0.005)	(0.005)	(0.005)	(0.005)
Age of household head (square term)			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Married household head			-0.095**	-0.089**	-0.088**	-0.090**
			(0.039)	(0.039)	(0.039)	(0.039)
Head or spouse with disability or chronic illness			0.075*	0.071	0.076*	0.072
			(0.044)	(0.044)	(0.044)	(0.044)
Business or wage employment			-0.003	-0.006	-0.005	-0.002
			(0.028)	(0.028)	(0.028)	(0.028)
Ganyu			0.028	0.034	0.03	0.03
			(0.030)	(0.031)	(0.030)	(0.030)
Household owns agricultural land			-0.069	-0.066	-0.066	-0.064
			(0.043)	(0.042)	(0.042)	(0.042)
Size of agricultural land used by household, in acre			-0.005	-0.004	-0.005	-0.005
			(0.003)	(0.003)	(0.003)	(0.003)
Number of 7 productive assets owned			0.010	0.008	0.000	0.002
			(0.016)	(0.015)	(0.015)	(0.015)
Number of 14 domestic assets owned			0.005	0.005	0.004	0.005
			(0.007)	(0.007)	(0.007)	(0.007)
Iron sheets as roof material			-0.037	-0.029	-0.017	-0.020
			(0.030)	(0.029)	(0.029)	(0.029)
Number of months with insufficient food, last 12 months			0.007	0.008*	0.004	0.004
			(0.005)	(0.005)	(0.005)	(0.005)
Voluntary community work, last 12 months			-0.018	-0.012	-0.007	-0.005
			(0.026)	(0.026)	(0.026)	(0.026)
Severely affected by drought, last past 12 months			-0.025	-0.025	-0.031	-0.03
			(0.026)	(0.026)	(0.026)	(0.026)
Main income earner died, last 12 months			0.05	0.044	0.033	0.042
			(0.095)	(0.096)	(0.094)	(0.094)
Other household member died, last 12 months			-0.102**	-0.102**	-0.090*	-0.090*
			(0.049)	(0.048)	(0.048)	(0.048)
Dwelling damaged, last 12 months			0.026	0.026	0.028	0.039
			(0.050)	(0.050)	(0.049)	(0.049)
Observations	924	924	920	920	920	920

Notes: All regressions are estimated with OLS. Standard errors are unclustered but robust to heteroscedasticity. *Control_M* denotes the control catchment that is located in the same district (namely Mchinji) as the treatment catchment.

Appendix 3.C: Participation in the enhanced capacity building activities, details

Figure C.3.2: Details about participation in the enhanced capacity building activities



Appendix 3.D: PW status, details

Table D.3.10: PW status, details

	Treatment catchment			Control catchments					All catchments
	All villages (1)	Special village (2)	Other villages (3)	All Controls (4)	Mchinji Control (5)	Kasungu Controls (6)	K_W (7)	K_L (8)	
MASAF-4 at baseline	0.42	0.03	0.54	0.53	0.51	0.54	0.59	0.51	0.49
Never-PW	0.38	0.44	0.36	0.37	0.43	0.35	0.32	0.37	0.38
Always-MASAF-4	0.33	0.00	0.43	0.47	0.41	0.50	0.53	0.48	0.42
MASAF-4 Dropout	0.09	0.03	0.11	0.06	0.10	0.05	0.07	0.03	0.07
MASAF-4 Entrants	0.07	0.00	0.09	0.09	0.06	0.10	0.08	0.12	0.08
IFA/Other Entrants	0.13	0.53	0.01	0.01	0.01	0.01	0.01	0.00	0.05
Observations	268	64	204	500	154	346	133	213	768

Notes: Special village denotes the village in the treatment catchment where no MASAF-4 subproject was implemented but a one-off work cycle under IFA, a different PWP. *K_W* denotes one of the control catchments located in Kasungu District and *K_L* the second one there

Appendix 3.E: Additional baseline summary statistics

See Tables Table E.3.11 and Table E.3.12..

Table E.3.11: Detailed baseline summary statistics and balancing tests, dependent variables and control variables

	Mean in control catchments (sd)		Difference in means				
	PW (1)	Non-PW (2)	All villages			Excl. special village	
			PW (3)	Non-PW (4)	Both (5)	Non-PW (6)	Both (7)
Asset vector: voluntary community work, last 12 months							
At least one workday in ...							
Any sector	0.60	0.52	0.09	0.08	0.09*	0.13	0.11*
Afforestation	0.04	0.02	0.03	0.02	0.03	0.02	0.02
Land conservation	0.02	0.01	-0.01	0.00	0.00	-0.01	-0.01
Nursery/seedling production	0.01	0.00	0.01	0.00	0.00	0.00	0.00
Road construction/maintenance	0.05	0.05	-0.21**	-0.11**	-0.16**	-0.15**	-0.18**
Other activities	0.38	0.37	0.18**	0.13*	0.15**	0.17**	0.18**
Number of community workdays in ...							
Total	6.47 (12.2)	5.86 (11.0)	-0.79	2.86*	1.23	2.96*	0.93
Afforestation	0.66 (3.9)	0.05 (0.5)	0.61	0.05	0.37	0.05	0.36
Land conservation	0.29 (2.8)	0.02 (0.2)	-0.04	0.00	0.01	-0.01	-0.02
Nursery/seedling production	0.14 (2.0)	0.00 (0.0)	0.14	0.00	0.08	0.00	0.08
Road construction/maintenance	0.63 (3.7)	0.65 (3.7)	-1.76**	-0.27	-0.96**	-0.52	-1.19**
Other activities	2.96 (7.1)	3.44 (7.5)	0.45	1.98*	1.22*	2.13*	1.21
Skills vector: individual SWC measures on private land							
Number of SWC measures	1.50 (1.0)	1.40 (0.9)	0.14	0.33**	0.25**	0.23	0.18*
Days worked on SWC, last 12 months	9.00 (12.3)	8.08 (10.7)	1.54	2.29	2.04*	2.08	1.81
Household has [...] on its private land							
Any SWC measures	0.83	0.83	0.02	0.12*	0.08*	0.07	0.04
Grass strips/barriers	0.36	0.30	0.11	0.11	0.12**	0.06	0.09*
Drainage/ditches/swales	0.06	0.10	0.00	0.07*	0.03	0.05	0.03
Contour bunds	0.33	0.31	-0.15*	0.02	-0.06	0.00	-0.08
Marker ridges	0.25	0.24	0.02	0.01	0.02	0.01	0.02
Box ridges	0.31	0.30	0.08	0.06	0.07	0.07	0.08
Manure used, last agric. season	0.57	0.46	0.28**	0.18**	0.24**	0.18**	0.24**
Control variables							
Household size	5.73 (2.2)	5.29 (2.3)	-0.87**	-0.28	-0.51**	-0.31	-0.61**
Maximum education level of head/spouse							
Primary completed	0.41	0.30	-0.06	-0.09	-0.07	-0.11	-0.08
Secondary completed or more	0.09	0.04	0.03	-0.01	0.01	-0.01	0.01
Age of household head (in years)	43.51 (14.8)	41.65 (15.6)	-2.19	0.68	-0.48	0.11	-1.12
Head/spouse with disability/chronic illness	0.08	0.12	0.01	0.03	0.02	0.04	0.02
Married household head	0.89	0.78	0.00	0.01	0.02	0.01	0.00
Number of months with insufficient food	3.88 (3.0)	3.64 (2.7)	1.40**	1.15**	1.29**	1.25**	1.33**
Number of 7 productive assets owned	1.15 (1.1)	0.94 (1.0)	0.48**	0.20	0.35**	0.27	0.39**
Number of 14 domestic assets owned	4.03 (2.2)	3.43 (2.1)	0.36	-0.35	0.04	-0.16	0.13
Business or wage employment	0.31	0.29	0.10	-0.03	0.03	-0.08	0.02

Notes: The first two columns on the left display the mean in the control catchments, with the standard deviation (sd) below in parentheses for non-binary variables. Difference in means indicate the difference between the mean of households from the control catchments and the mean of households from the treatment catchment, respectively for Always-MASAF-4 households (*PW*), Never-*PW* households (*Non-PW*), and both groups combined (*Both*). Asterisks indicate the significance level of differences in means as determined by the t-tests: * for $p < .05$ and ** for $p < .01$

Table E.3.12: Baseline summary statistics and balancing tests, additional household characteristics

	Mean in control catchments (sd)		Difference in means				
	PW	Non-PW	PW	Non-PW	Both	Excl. special village	
						Non-PW	Both
Household farms	0.99	0.95	0.00	-0.02	-0.01	-0.02	-0.01
Activity among two main economic activities, last 12 months							
Crop production	0.80	0.72	-0.03	-0.07	-0.05	-0.05	-0.04
Agricultural piecework (ganyu)	0.62	0.59	0.08	0.08	0.08	0.13*	0.10*
Business	0.27	0.23	0.06	-0.08	-0.01	-0.12*	-0.02
Wage employment	0.04	0.07	0.04	0.06*	0.05**	0.06	0.05*
Wealth proxies							
Number of 22 assets owned	5.19 (3.0)	4.37 (2.8)	0.85*	-0.15	0.39	0.11	0.52*
Household has/owns ...							
House they live in	0.94	0.96	-0.04	0.00	-0.02	0.02	-0.02
Iron sheets as roof material	0.29	0.21	-0.03	-0.03	-0.02	-0.08	-0.05
Electricity in dwelling	0.10	0.05	0.08*	0.02	0.05*	0.01	0.05*
Bicycle	0.37	0.31	0.00	-0.05	-0.02	0.00	0.00
Motorcycle/scooter	0.03	0.04	-0.01	0.01	0.00	0.00	0.00
Radio	0.31	0.26	0.14*	0.04	0.09*	0.06	0.10*
Television	0.05	0.04	0.02	0.01	0.02	0.00	0.01
Solar panel	0.20	0.15	0.17**	0.04	0.11**	0.04	0.11**
Cell phone	0.51	0.39	0.28**	0.24**	0.27**	0.24**	0.26**
Any livestock	0.63	0.58	0.11	0.14*	0.13**	0.15*	0.13**
Goats	0.25	0.25	0.01	0.08	0.05	0.06	0.03
Pigs	0.10	0.07	0.08*	0.04	0.06**	0.03	0.06*
Cattle	0.04	0.04	-0.08*	-0.04	-0.05**	-0.05	-0.06**
Chickens	0.49	0.47	0.16*	0.19**	0.17**	0.20**	0.18**
Shocks and support							
Affected by irregular rain, last 12 months	0.42	0.41	0.20**	0.15**	0.18**	0.23**	0.21**
Number of months with insufficient food	3.88 (3.0)	3.64 (2.7)	1.40**	1.15**	1.29**	1.25**	1.33**
Household received ...							
Any social assistance	0.42	0.32	0.36**	0.20**	0.29**	0.19**	0.28**
MVAC emergency assistance	0.30	0.19	0.29**	0.19**	0.25**	0.19**	0.25**
Any subsidised fertiliser	0.18	0.16	0.16**	0.07	0.11**	0.05	0.11**
School meals	0.15	0.14	-0.01	0.11**	0.05	0.09*	0.04
Agricultural information							
Size of agric. land used, in acre	3.48 (4.3)	2.77 (2.7)	0.60	0.30	0.51	0.46	0.55
Rents agric. land for money	0.26	0.22	0.04	0.02	0.03	-0.02	0.02
Used fertiliser, last agric. season	0.77	0.80	-0.13*	0.04	-0.04	0.08	-0.03
Irrigates using gravity or pumps	0.00	0.01	-0.13**	-0.10**	-0.12**	-0.09**	-0.11**
Got agricultural extension, last 12 months	0.37	0.23	0.10	0.01	0.07	0.08	0.09*
Planted trees, last 2 years	0.36	0.25	0.15*	0.12*	0.14**	0.12*	0.14**
Removed trees, last 2 years	0.33	0.28	0.15*	0.04	0.10*	0.05	0.11*
Any soil erosion on agric. land	0.76	0.78	-0.10	-0.03	-0.06	-0.04	-0.07
Soil erosion on entire agric. land	0.13	0.19	-0.05	-0.05	-0.06	-0.07	-0.06

Notes: The first two columns on the left display the mean in the control catchments, with the standard deviation (sd) below in parentheses for non-binary variables. Difference in means indicate the difference between the mean of households from the control catchments and the mean of households from the treatment catchment, respectively for Always-MASAF-4 households (*PW*), Never-PW households (*Non-PW*), and both groups combined (*Both*). Asterisks indicate the significance level of differences in means as determined by the t-tests: * for p<.05 and ** for p<.01

Appendix 3.F: Survey questions

Table F.3.13: Voluntary community work indicators

Baseline (Feb 2017)	Endline 2 (Feb 2019)
At any time over the last 12 months, did anyone in your household work in a community activity for nothing specific in return?	
For how many days in total?	
How many days did you work in [COMMUNITY ACTIVITY] in the last 12 months for nothing specific in return?	How many days did you work in [COMMUNITY ACTIVITY] in the last 12 months for nothing specific in return?
Farming	1 Farming
Afforestation	2 Afforestation
Irrigation	3 Irrigation
Land conservation	4 Land conservation
Road construction/maintenance	5 Road construction/maintenance
Fisheries	6 Fisheries
Nursery/seedling production	7 Nursery/seedling production
Other [SPECIFY]	8 School-related constr. activities
School	9 School-related non-constr. activities
Construction	11 Hospital construction
	10 Other activities [SPECIFY]

Notes: All regression estimates draw only on the information regarding the 12 months prior to the respective survey wave. Hence, the periods compared are 'Feb 2016 to Feb 2017' (BL) and 'Feb 2018 to Feb 2019' (EL). The intermediate period 'Feb 2017 to Feb 2018' is not considered even though the endline questionnaire included additional questions in reference to it. BL categories 'School' and 'Construction' are recoded from string information. To match BL and EL information for the categories 'Other', 'School' and 'Construction', categories are recoded and combined as follows. The EL categories (8) to (11) are combined to match BL category 'Other'. EL categories (8) and (9) are combined to match BL category 'School'. EL categories (8) and (11) are combined to match BL category 'Construction'.

Table F.3.14: SWC indicators

Baseline (Feb 2017)	Endline 2 (Feb 2019)
What types of measures are you using to control soil erosion?	Are you using [MEASURE] on your agricultural land?
1 Stone terraces	1 Stone terraces
2 Fanya juu/chini	2 Fanya juu/chini
3 Other terrace	3 Other terrace
4 Grass strips/barriers	4 Grass strips/barriers
5 Drainage/ditches	5 Drainage/ditches
6 Trash lines	6 Trash lines
7 Planting trees	7 Planting trees
8 Ripping	8 Ripping
9 Contour bunds	9 Contour bunds
10 Marker ridges	10 Marker ridges
11 Ditches/swales	11 Ditches/swales
12 Box ridges	12 Box ridges
13 Other [SPECIFY]	13 Other (SPECIFY)
14 None	15 Sandbag barriers; 16 Filtration pits; 17 Half-moons
(LIST UP TO THREE MEASURES)	
Last year, how many labour days did your household spend on construction and maintenance activities related to these measures on your agricultural land?	
Did you apply manure to your plots?	Did you apply manure to your plots during the last agricultural season (i.e., 2017/2018)?
1 Yes, on all of them	1 Yes, on all of them
2 Yes, on most of them	2 Yes, on most of them
3 Yes, on some of them	3 Yes, on some of them
4 No	4 No
[Additionally: How often do you apply manure on this plot? 1 Every year; 2 Most years; 3 Some years; 4 Rarely; 5 Just once]	[Same question was asked with respect to the agricultural seasons 2016/2017 and 2018/2019.]

Notes: The dependent variable *number of SWC measures* is the total of specific SWC measures reported. Manure is not included. At BL, responses were limited to three measures whereas at EL respondents were asked to select all that apply. Hence, some of the increase from baseline to endline is mechanic. The dependent variable *drainage* is the composite of the survey responses drainage/ditches and ditches/swales. For the dependent variable *use of manure*, the regression estimates are based on the most recently completed agricultural seasons prior to the respective survey, i.e., season 2015/2016 (BL) and season 2017/2018 (EL).

Appendix 3.G: Asset vector: additional estimation results

Table G.3.15: Voluntary community contributions, detailed estimation results for all sectors combined and afforestation

	All sectors				Afforestation			
	ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD								
A1: PW	20.411 (3.491)*** (1.151)***	20.303 (3.315)*** (1.507)***	25.781 (4.522)*** (1.247)***	25.494 (4.212)*** (1.607)***	5.210 (1.218)*** (0.126)***	4.657 (1.184)*** (0.251)***	6.563 (1.541)*** (0.133)***	5.848 (1.497)*** (0.290)***
A2: Non-PW	7.064 (2.404)*** (2.261)*	6.413 (2.315)*** (2.716)*	15.002 (5.118)*** (4.152)***	13.644 (4.957)*** (5.010)***	4.383 (1.047)*** (0.198)***	3.861 (0.944)*** (0.452)***	9.402 (2.350)*** (0.358)***	8.214 (2.117)*** (0.845)***
A3: Both	13.251 (2.172)*** (1.737)***	13.213 (2.063)*** (1.692)***	21.373 (3.468)*** (2.403)***	21.240 (3.289)*** (2.427)***	4.755 (0.805)*** (0.137)***	4.653 (0.800)*** (0.166)***	7.669 (1.323)*** (0.190)***	7.480 (1.320)*** (0.253)***
Panel B: DDD								
Treat*PW*End	13.947 (4.255)*** (1.634)***	13.955 (4.096)*** (2.033)***	11.812 (6.862)* (3.710)***	11.84 (6.676)* (4.279)***	0.731 (1.585) (0.164)**	0.873 (1.528) (0.376)	-2.927 (2.782) (0.324)***	-2.562 (2.704) (0.644)***
Treat*End	6.788 (2.407)*** (2.613)*	6.801 (2.368)*** (2.681)*	14.334 (5.119)*** (4.792)***	14.29 (5.066)*** (5.046)***	4.43 (1.044)*** (0.204)***	4.271 (0.992)*** (0.294)***	9.44 (2.340)*** (0.368)***	9.044 (2.265)*** (0.571)***
PW*End	0.866 (2.013) (1.724)	0.831 (1.982) (1.927)	0.856 (1.997) (1.479)	0.876 (1.967) (1.731)	0.22 (0.585) (0.174)	0.318 (0.605) (0.237)	0.203 (0.581) (0.154)	0.33 (0.599) (0.222)
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The unit of the dependent variables are the number of workdays in the respective sector during the last 12 months. To mitigate distortion by outliers, values were winsorised at fraction 0.98. The underlying sample includes observations from the special village. The outcome *all sectors* also includes workdays in these sectors. Means at baseline for the samples are reported in Table 3.4 in Section 3.4.2 and not repeated here.

Table G.3.16: Voluntary community contributions, detailed estimation results for land conservation and nursery

	Land conservation				Nursery/seedling production			
	ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD								
A1: PW	10.677 (1.649)*** (0.275)***	10.358 (1.620)*** (0.516)***	13.481 (2.194)*** (0.301)***	13.007 (2.148)*** (0.610)***	4.070 (1.225)*** (0.683)***	4.036 (1.212)*** (0.769)**	5.132 (1.547)*** (0.738)***	5.068 (1.534)*** (0.849)***
A2: Non-PW	6.949 (1.311)*** (0.302)***	6.564 (1.245)*** (0.420)***	14.938 (2.993)*** (0.609)***	13.965 (2.858)*** (0.731)***	2.494 (0.821)*** (0.127)***	2.107 (0.688)*** (0.337)***	5.355 (1.788)*** (0.216)***	4.484 (1.515)*** (0.621)***
A3: Both	8.713 (1.042)*** (0.241)***	8.477 (1.012)*** (0.289)***	14.058 (1.770)*** (0.338)***	13.628 (1.720)*** (0.457)***	3.117 (0.746)*** (0.342)***	3.233 (0.759)*** (0.324)***	5.029 (1.205)*** (0.474)***	5.197 (1.222)*** (0.463)***
Panel B: DDD								
Treat*PW*End	3.734 (2.102)* (0.263)***	3.973 (2.046)* (0.568)***	-1.317 (3.711) (0.443)***	-0.651 (3.635) (0.860)	1.586 (1.497) (0.591)*	2.021 (1.432) (0.752)*	-0.15 (2.390) (0.643)	0.519 (2.260) (0.909)
Treat*End	6.948 (1.309)*** (0.282)***	6.62 (1.257)*** (0.367)***	14.803 (2.983)*** (0.537)***	13.994 (2.881)*** (0.710)***	2.48 (0.832)*** (0.172)***	2.376 (0.774)*** (0.187)***	5.28 (1.803)*** (0.307)***	5.018 (1.692)*** (0.379)***
PW*End	-0.239 (0.380) (0.241)	-0.208 (0.424) (0.347)	-0.276 (0.379) (0.181)	-0.184 (0.419) (0.326)	1.236 (0.492)** (0.632)	1.126 (0.501)** (0.614)	1.225 (0.488)** (0.541)**	1.136 (0.497)** (0.542)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The unit of the dependent variables are the number of workdays in the respective sector during the last 12 months. To mitigate distortion by outliers, values were winsorised at fraction 0.98. The underlying sample includes observations from the special village. The outcome *all sectors* also includes workdays in these sectors. Means at baseline for the samples are reported in Table 3.4 in Section 3.4.2 and not repeated here.

Table G.3.17: Voluntary community contributions, detailed estimation results for non-watershed management-related sectors

	Roads				Other (mostly school-related)			
	ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD								
A1: PW	0.152 (1.113) (0.418)	0.089 (1.033) (0.531)	0.213 (1.402) (0.446)	0.112 (1.282) (0.572)	-3.806 (1.591)** (1.078)**	-4.038 (1.501)*** (0.890)**	-4.816 (1.998)** (1.171)***	-5.071 (1.903)*** (0.974)***
A2: Non-PW	-0.446 (0.818) (1.627)	-0.691 (0.826) (1.758)	-0.954 (1.725) (2.963)	-1.455 (1.741) (3.166)	-1.756 (1.492) (2.358)	-2.199 (1.369) (2.636)	-3.910 (3.294) (4.390)	-4.678 (2.871) (4.787)
A3: Both	-0.127 (0.676) (0.793)	-0.174 (0.655) (0.815)	-0.206 (1.082) (1.095)	-0.279 (1.043) (1.122)	-2.636 (1.076)** (1.629)	-2.569 (1.028)** (1.623)	-4.262 (1.760)** (2.271)*	-4.130 (1.651)** (2.243)*
Panel B: DDD								
Treat*PW*End	0.792 (1.393) (1.671)	0.883 (1.357) (1.770)	1.484 (2.248) (3.011)	1.636 (2.220) (3.089)	-1.664 (2.187) (1.687)	-1.407 (2.061) (2.141)	-0.437 (3.881) (3.695)	-0.125 (3.533) (4.299)
Treat*End	-0.551 (0.829) (1.678)	-0.617 (0.833) (1.665)	-1.175 (1.750) (3.048)	-1.302 (1.762) (3.022)	-1.864 (1.494) (2.526)	-1.93 (1.405) (2.715)	-4.029 (3.315) (4.658)	-4.079 (2.968) (4.953)
PW*End	-0.507 (0.731) (1.736)	-0.461 (0.767) (1.847)	-0.509 (0.724) (1.486)	-0.461 (0.761) (1.589)	-0.079 (1.491) (1.716)	-0.192 (1.398) (1.738)	-0.044 (1.477) (1.469)	-0.199 (1.388) (1.488)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Mean at baseline								
PW, treatment			2.39					2.51
PW, control			0.63					2.96
Non-PW, treatment			0.92					1.46
Non-PW, control			0.65					3.44
Both, treatment			1.60					1.95
Both, control			0.64					3.17

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The unit of the dependent variables are the number of workdays in the respective sector during the last 12 months. To mitigate distortion by outliers, values were winsorised at fraction 0.98. The underlying sample includes observations from the special village.

Appendix 3.H: Skills vector: additional estimation results

Table H.3.18: SWC adoption, detailed estimation results for non-binary outcomes

	Number of SWC measures				Number of SWC workdays, last 12 months			
	ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD								
A1: PW	0.062 (0.186) (0.047)	0.087 (0.091) (0.068)	0.078 (0.232) (0.049)	0.110 (0.113) (0.074)	1.831 (1.932) (1.017)	1.294 (1.897) (1.289)	2.289 (2.389) (1.095)**	1.604 (2.327) (1.373)
A2: Non-PW	0.150 (0.176) (0.015)***	0.157 (0.086)* (0.023)***	0.312 (0.389) (0.031)***	0.339 (0.183)* (0.043)***	2.600 (1.393)* (0.932)*	2.258 (1.345)* (0.722)*	5.513 (3.014)* (1.675)***	4.836 (2.892)* (1.336)***
A3: Both	0.100 (0.128) (0.026)**	0.109 (0.062)* (0.046)*	0.161 (0.208) (0.035)***	0.176 (0.099)* (0.063)***	2.181 (1.166)* (0.947)	1.737 (1.110) (1.142)	3.510 (1.874)* (1.309)***	2.761 (1.763) (1.555)*
Panel B: DDD								
Treat*PW *End	-0.101 (0.256) (0.030)**	-0.111 (0.125) (0.018)***	-0.263 (0.455) (0.037)***	-0.295 (0.217) (0.019)***	-0.537 (2.388) (0.530)	-0.999 (2.344) (0.752)	-2.832 (3.874) (0.894)***	-3.180 (3.757) (0.393)***
Treat*End	0.158 (0.178) (0.023)***	0.173 (0.087)** (0.038)**	0.335 (0.391) (0.040)***	0.374 (0.184)** (0.070)***	2.443 (1.388)* (0.772)	2.214 (1.337)* (0.631)*	5.225 (3.024)* (1.826)***	4.695 (2.878) (1.477)***
PW*End	0.139 (0.137) (0.031)**	0.145 (0.067)** (0.030)**	0.141 (0.136) (0.027)***	0.146 (0.066)** (0.026)***	0.091 (1.288) (0.492)	0.073 (1.238) (0.756)	0.101 (1.279) (0.422)	0.074 (1.228) (0.644)
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. The dependent variable *number of SWC measures* was modified based on the assumption that SWC measures that were there reported at baseline are still there at endline even if it was not reported. The underlying sample includes observations from the special village. Households that either did not farm at baseline or endline are disregarded. Means at baseline for the samples are reported in Section 3.4.3 and not repeated here.

Table H.3.19: SWC adoption, detailed estimation results for binary outcomes

	Any SWC measure				Drainage				Box ridges				Manure			
	ITT		IV		ITT		IV		ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD																
A1: PW	-0.004 (0.063) (0.036)	0.001 (0.038) (0.026)	-0.005 (0.078) (0.039)	0.001 (0.048) (0.028)	0.000 (0.051) (0.012)	0.014 (0.028) (0.005)*	0.000 (0.063) (0.013)	0.017 (0.036) (0.006)***	0.004 (0.080) (0.030)	0.013 (0.029) (0.024)	0.004 (0.100) (0.032)	0.017 (0.036) (0.026)	0.141 (0.084)* (0.040)**	0.160 (0.076)** (0.044)**	0.175 (0.109) (0.044)***	0.202 (0.095)** (0.047)***
A2: Non-PW	0.066 (0.070) (0.023)*	0.063 (0.038)* (0.022)*	0.136 (0.154) (0.040)***	0.137 (0.082)* (0.041)***	0.071 (0.055) (0.013)**	0.065 (0.039)* (0.009)***	0.152 (0.118) (0.027)***	0.140 (0.085)* (0.016)***	0.047 (0.081) (0.009)**	0.049 (0.028)* (0.008)***	0.098 (0.174) (0.019)***	0.106 (0.058)* (0.015)***	0.012 (0.085) (0.052)	-0.009 (0.072) (0.065)	0.018 (0.187) (0.093)	-0.019 (0.155) (0.120)
A3: Both	0.030 (0.047) (0.029)	0.028 (0.027) (0.023)	0.047 (0.077) (0.040)	0.045 (0.043) (0.032)	0.037 (0.037) (0.009)**	0.048 (0.025)* (0.008)**	0.059 (0.059) (0.013)***	0.077 (0.040)* (0.012)***	0.027 (0.056) (0.011)*	0.030 (0.020) (0.009)**	0.043 (0.091) (0.016)***	0.049 (0.031) (0.013)***	0.070 (0.060) (0.032)	0.075 (0.053) (0.029)*	0.113 (0.101) (0.045)**	0.120 (0.084) (0.040)***
Panel B: DDD																
Treat*PW *End	-0.010 (0.099) (0.017)	-0.019 (0.052) (0.013)	-0.019 (0.233) (0.014)	-0.047 (0.111) (0.013)***	-0.076 (0.074) (0.023)*	-0.071 (0.048) (0.019)*	-0.160 (0.133) (0.045)***	-0.162 (0.092)* (0.040)***	-0.035 (0.113) (0.025)	-0.038 (0.041) (0.024)	-0.085 (0.200) (0.033)***	-0.092 (0.071) (0.033)***	0.122 (0.119) (0.080)	0.145 (0.104) (0.078)*	0.143 (0.218) (0.150)**	0.178 (0.181) (0.145)**
Treat*End	0.006 (0.077) (0.020)	0.015 (0.036) (0.016)	0.013 (0.220) (0.048)	0.041 (0.101) (0.038)	0.073 (0.055) (0.015)**	0.081 (0.039)** (0.016)**	0.156 (0.118) (0.039)***	0.175 (0.085)** (0.037)***	0.046 (0.081) (0.007)***	0.050 (0.028)* (0.006)***	0.099 (0.174) (0.017)***	0.107 (0.059)* (0.016)***	0.014 (0.085) (0.055)	0.007 (0.072) (0.052)	0.027 (0.190) (0.130)	0.014 (0.155) (0.123)
PW*End	0.028 (0.047) (0.016)	0.036 (0.027) (0.012)*	0.029 (0.047) (0.014)**	0.036 (0.027) (0.010)***	-0.001 (0.044) (0.023)	-0.006 (0.022) (0.021)	-0.001 (0.043) (0.020)	-0.005 (0.022) (0.018)	0.022 (0.066) (0.021)	0.019 (0.018) (0.021)	0.023 (0.065) (0.018)	0.019 (0.018) (0.018)	0.021 (0.070) (0.088)	0.016 (0.062) (0.081)	0.022 (0.069) (0.076)	0.017 (0.061) (0.070)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The reported dependent variables (except the number of SWC workdays, where it does not apply) are modified based on the assumption that SWC measures that were there reported at baseline are still there at endline even if it was not reported. The underlying sample includes observations from the special village. Households that either did not farm at baseline or endline are disregarded. Means at baseline for the samples are reported in Section 3.4.3 and not repeated here.

Table H.3.20: Adoption of SWC measures, detailed estimation results for additional outcomes

	Grass barriers				Contour bunds				Marker ridges			
	ITT		IV		ITT		IV		ITT		IV	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (1)	FE (2)	OLS (3)	FE (4)
Panel A: DiD												
A1: PW	-0.023 (0.084) (0.059)	-0.009 (0.054) (0.052)	-0.031 (0.106) (0.063)	-0.012 (0.068) (0.056)	0.013 (0.090) (0.005)*	0.009 (0.045) (0.013)	0.018 (0.112) (0.005)***	0.012 (0.056) (0.014)	0.027 (0.080) (0.020)	0.018 (0.030) (0.012)	0.034 (0.099) (0.021)	0.023 (0.037) (0.013)*
A2: Non-PW	0.019 (0.082) (0.013)	0.025 (0.050) (0.022)	0.036 (0.176) (0.021)*	0.055 (0.107) (0.040)	-0.003 (0.084) (0.029)	0.003 (0.040) (0.026)	-0.007 (0.179) (0.052)	0.006 (0.085) (0.048)	-0.023 (0.075) (0.007)*	-0.016 (0.018) (0.010)	-0.050 (0.160) (0.014)***	-0.036 (0.038) (0.018)*
A3: Both	-0.007 (0.058) (0.034)	-0.007 (0.037) (0.036)	-0.012 (0.095) (0.046)	-0.011 (0.059) (0.049)	-0.001 (0.062) (0.013)	0.004 (0.029) (0.015)	-0.001 (0.099) (0.017)	0.006 (0.047) (0.020)	0.004 (0.055) (0.007)	0.000 (0.016) (0.010)	0.006 (0.087) (0.009)	0.000 (0.026) (0.013)
Panel B: DDD												
Treat*PW*End	-0.042 (0.118) (0.045)	-0.043 (0.072) (0.037)	-0.068 (0.207) (0.042)**	-0.071 (0.125) (0.052)**	0.006 (0.123) (0.021)*	0.000 (0.060) (0.025)	0.013 (0.212) (0.053)***	-0.005 (0.102) (0.058)**	0.039 (0.109) (0.022)*	0.035 (0.034) (0.018)*	0.063 (0.190) (0.032)***	0.059 (0.053) (0.036)***
Treat*End	0.018 (0.082) (0.012)	0.019 (0.050) (0.028)	0.038 (0.177) (0.027)***	0.041 (0.106) (0.068)	-0.004 (0.084) (0.025)*	0.005 (0.040) (0.025)	-0.009 (0.181) (0.058)***	0.012 (0.085) (0.060)**	-0.014 (0.076) (0.009)**	-0.016 (0.017) (0.014)	-0.031 (0.162) (0.019)***	-0.035 (0.037) (0.035)**
PW*End	0.068 (0.068) (0.047)	0.071 (0.040)* (0.039)	0.068 (0.068) (0.040)*	0.071 (0.040)* (0.033)**	0.018 (0.069) (0.017)	0.020 (0.032) (0.020)	0.018 (0.068) (0.015)	0.020 (0.032) (0.017)	0.007 (0.063) (0.019)	0.008 (0.018) (0.014)	0.007 (0.062) (0.016)	0.008 (0.018) (0.012)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean at baseline												
PW, treatment			0.25				0.48				0.23	
PW, control			0.36				0.33				0.25	
Non-PW, treatment			0.19				0.29				0.23	
Non-PW, control			0.30				0.31				0.24	
Both, treatment			0.22				0.39				0.23	
Both, control			0.34				0.33				0.25	

Notes: * for $p < .1$, ** for $p < .05$, *** for $p < .01$. Standard errors are reported in parentheses below the coefficients for two different methods: unclustered heteroscedasticity-robust standard errors in the first row and standard errors clustered at the catchment level in the second row. The reported dependent variables are modified based on the assumption that SWC measures that were there reported at baseline are still there at endline even if it was not reported. The underlying sample includes observations from the special village. Households that either did not farm at baseline or endline are disregarded.

Appendix 3.I: Checking robustness to issues concerning the data on SWC adoption

As an additional robustness check, I show that two potential problems concerning data (collection) on SWC adoption do not affect the results presented in Section 3.4.3. First, in the baseline questionnaire, the number of types of SWC measures respondents could list was limited to three (due to time constraints). In the endline questionnaire, the limit was removed, and respondents were asked to list all measures that apply. Hence, in cases where respondents listed exactly three SWC measures at baseline, changes in adoption in the data may be an artifact of the changed format of the question. Columns 1 and 2 of Table I.3.21. show the number of new adoptions for each outcome (i.e., cases where the data show an increase from baseline to endline). Columns 3 and 4 display the share of these new adoptions that coincides with having three SWC measures at baseline. Differences in shares are calculated in Column 5. Overall, the overlap between new adoptions and cases with three SWC measures at baseline is small. The highest overlap is 20% for marker ridges in the control catchments. For the rest, the share is close to, and often well below, 10%. Differences between treatment and control catchments are all below 10 pp. Hence, this difference in the questionnaires cannot drive the results.

Table I.3.21: New adoption coinciding with three SWC measures at baseline

	Number of new adoptions		Share of adoptions coinciding with three SWC measures		Difference
	Treatment (1)	Control (2)	Treatment (3)	Control (4)	T - C (5)
Number of SWC measures	135	221	0.09	0.11	-0.02
Any SWC measure	27	43	0.00	0.00	0.00
Drainage	24	26	0.13	0.04	0.09
Grass strips/barriers	53	104	0.06	0.02	0.04
Contour bunds	35	63	0.09	0.11	-0.03
Marker ridges	9	20	0.11	0.20	-0.09
Box ridges	18	18	0.06	0.11	-0.06
Manure	73	118	0.05	0.14	-0.08

Notes: Households that did not farm at baseline or endline are excluded. Only *number of SWC measures* is non-binary.

Second, there are many cases where a SWC measure was reported to have been on a household's land at baseline but at endline it was no longer reported. In total, 65% of observations are potentially affected. Enquiries with the enumerators confirmed that they mostly only reported new measures during the endline survey. In my preferred specifications, endline observations are, therefore, recoded such that all measures that were listed at baseline are assumed to be still there at endline, irrespective of whether it was reported as such. I checked that the findings in Section 3.4.3 are robust to using the original observations and to limiting the analysis for each outcome to observations where there are no differences between the original data and the recoded data. These estimation results are available upon request.

Appendix 3.J: Shocks, support, and extension services during intervention period

Table J.3.22: Shocks, support, and agricultural extension services (AES) during the intervention period

	Both		Non-PW		PW	
	Mean (sd)	Diff	Mean (sd)	Diff	Mean (sd)	Diff
In the last 24 months, household was severely affected by ...						
High prices for agricultural input	0.61	-0.09*	0.57	-0.16**	0.64	-0.03
High prices for food	0.45	-0.05	0.44	-0.11	0.45	0.02
Low prices for agricultural output	0.37	0.07	0.34	0.04	0.40	0.10
Drought	0.27	0.12**	0.25	0.09	0.29	0.15**
Irregular rains	0.24	0.10**	0.22	0.09	0.26	0.12*
Crop pest	0.17	-0.07*	0.17	-0.08	0.17	-0.06
Severe water shortage	0.10	0.09**	0.12	0.10**	0.08	0.08**
Serious illness or accident of household member(s)	0.10	-0.15**	0.10	-0.14**	0.10	-0.15**
Livestock pest	0.09	-0.01	0.07	0.00	0.09	-0.02
Dwelling damaged, destroyed	0.05	-0.01	0.04	-0.05	0.06	0.03
Death of other household member(s)	0.04	-0.03	0.04	-0.01	0.03	-0.05
Theft of money/ valuables/ assets/agricultural output	0.04	-0.01	0.04	-0.01	0.04	-0.02
Land loss	0.02	-0.01	0.03	0.02	0.01	-0.04*
In the last 24 months, household received income or support from ...						
Any social assistance (excl. PW)	0.25	0.20**	0.20	0.18**	0.29	0.21**
Any subsidised fertiliser	0.10	0.06*	0.06	0.05*	0.13	0.05
Emergency food assistance	0.14	0.14**	0.09	0.09**	0.18	0.18**
Other project (run by government, NGOs, or others)	0.01	0.01	0.01	0.01	0.01	0.01
In the last 24 months, household received any AES	0.42	-0.08	0.30	-0.08	0.51	-0.12
Last 24 months, AES received from ...						
Friend	0.08	-0.13**	0.07	-0.13**	0.09	-0.15**
Model farmer	0.02	0.02	0.00	-0.01	0.04	0.04
Other farmer	0.01	-0.04**	0.01	-0.06**	0.02	-0.03
Farmer group	0.00	0.00	0.00	0.00	0.01	0.00
Government extension worker	0.27	-0.10*	0.15	-0.06	0.37	-0.20**
Non-government extension worker	0.11	0.10**	0.10	0.10**	0.12	0.09*
AES received regarding ...						
Planting	0.24	0.00	0.16	-0.06	0.30	0.03
Manure	0.17	-0.04	0.10	-0.04	0.23	-0.07
Use of seeds	0.16	0.01	0.10	-0.03	0.21	0.02
Use of fertiliser	0.13	-0.02	0.08	-0.05	0.18	-0.01
Natural resource management	0.10	-0.15**	0.04	-0.12**	0.14	-0.20**
Use of chemicals	0.06	0.00	0.03	-0.03	0.08	0.03
Post-harvest services	0.05	0.02	0.03	0.02	0.06	0.03
Other AES	0.05	0.02	0.03	0.02	0.07	0.02
Irrigation	0.02	-0.07**	0.02	-0.04*	0.02	-0.09**
Livestock management	0.02	-0.02	0.02	0.00	0.02	-0.05*

Notes: Types of shocks that did not affect more than 5% of households are not reported. *Difference* denotes the difference between the mean of households from the control catchments and the mean of households from the treatment catchment, respectively for Always-MASAF-4 households (*PW*), Never-PW households (*Non-PW*), and both groups combined (*Both*). Asterisks indicate the significance level of differences in means as determined by the t-tests: * for p<.05 and ** for p<.01

4 Public Works Programmes and Cooperation for the Common Good: Evidence from Malawi

With Marina Dodlova

4.1 Introduction

It has long been understood that social cohesion is needed for societies to be successful (Knack & Keefer, 1997; Nosratabadi et al., 2020).⁵⁴ Strong reciprocal relationships and joint community activities can serve as a cushion that insures people against shocks by providing mutual financial and social support during times of need. They are also important in the face of large collective challenges such as the COVID-19 pandemic, climate change, and scarcity of common resources. One potential channel to build or maintain social cohesion is social protection. There is a long-running debate about the relationship between social protection (usually under the label *welfare state*) and social cohesion in developed countries (Ferragina, 2017; Kumlin & Rothstein, 2005; Rothstein, 2001). Yet, evidence from developing countries has only recently begun to emerge.

Social protection programmes have been widely discussed in the context of reducing poverty and improving nutrition, human capital, and well-being. However, their effects on social cohesion have not been properly studied. We address this gap by investigating the relationship between Malawi's largest and oldest social protection programme, the MASAF Public Works Programme (PWP), and social cohesion. We use the conceptualisation by Burchi et al. (forthcoming) that distinguishes three attributes of social cohesion: cooperation for the common good, inclusive identity, and trust. In this paper, we focus on the first attribute, specifically on within-community coordination and contributions to local public goods.

⁵⁴ Here and thereafter, we use the terms social cohesion and social capital interchangeably and draw on both strands of the literature.

The large majority of existing studies on the relationship between social protection and social cohesion concern cash transfer programmes, whereas PWPs, another popular social protection instrument, have so far received less attention. PWPs are transfer programmes that require participants to work on public projects for wages that are deliberately set below the market rate or at the level of the minimum wage. This principle is meant to ensure that only those in need enrol while the non-poor are discouraged from programme participation. The few studies that investigate the relationship between PWPs and social cohesion find positive associations with horizontal dimensions of social cohesion in the context of India's rural employment guarantee scheme (Bhuwania et al., 2016) and for a cash-for-work programme in a refugee context in Jordan (Loewe et al., 2020). However, to the best of our knowledge, there are no quantitative studies that evaluate the effects of a PWP on any of the attributes or dimensions of social cohesion in the African context; especially none that investigate the relationship between public works and cooperation for the common good outside the framework of the PWP.

As in the existing studies, endogeneity concerns prevent a rigorous identification of causal PWP effects on social capital because neither the assignment of the MASAF PWP to communities nor the enrolment of households in the programme is randomised. As a second-best approach, we triangulate correlational results of fixed effects panel analyses for a set of outcomes and sectors using two datasets with different units of analysis (households and communities). We cannot rule out that our estimates are biased by unobserved factors that affect both PWP status and cooperation for the common good of an observation unit. Yet, relying exclusively on within-unit variation, which is what fixed effects panel analysis implies, mitigates the risk of bias caused by non-random programme assignment.

The household-level primary data was collected in two waves (2017 and 2019) from randomly selected households who live in three purposely selected catchments (clusters of villages) where the MASAF-4 PWP was implemented. The community-level secondary data of the Integrated Household Survey (IHS) was collected in 2010, 2013, and 2016. Our notion of cooperation for the common good in this paper comprises within-community coordination and contributions to local public goods. We measure *coordination* through meeting activities linked to addressing common

needs and *contributions* through voluntary unpaid labour contributions to communal activities and other in-kind contributions for community purposes. While indicators of coordination are only available in the secondary data, indicators of contributions are available in both samples. In addition, we disentangle in both samples the sectors in which cooperation takes place (e.g., school, roads, water, health, and land management).

We find a positive association between PWPs and cooperation for the common good. The association is quite robust across different outcomes and samples. Specifically, we find that PWPs are positively associated with overall coordination among community members as well as top-down and bottom-up cooperation in specific sectors like agriculture, public transportation and bridges, school-building activities, and care. In the presence of PWPs, voluntary contributions are also higher in specific sectors, especially for school-building activities where we find a positive association in both samples.

Our results contribute to a better understanding of how social protection programmes with community-driven features are linked to social cohesion across sectors and along both horizontal and vertical lines in a developing country context, particularly in settings with a relatively homogenous population unaffected by violent conflict. The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the Malawian context. Section 4 presents the data, sample properties, and methodology. Section 5 reports and discusses the results. Section 6 concludes.

4.2 Literature review

Literature on the relationship between PWPs and social cohesion is scarce, but the literature on CDD projects that promote the provision of public goods and on cash transfers can inform the discussion because, notwithstanding some key differences, both types of intervention share important features of PWPs. The crucial difference to the former is the remuneration of work and to the latter the work component. Evidence regarding their respective effect on social cohesion, including cooperation for the common good, is mixed for both cash transfers and CDD projects.

For a CDD project in Morocco, Nguyen and Rieger (2017) find increased contributions in public goods games. However, two reviews of existing studies conclude that CDD projects rarely have positive effects on social cohesion (King et al., 2010; H. White et al., 2018). In particular, with two exceptions, CDD projects did not increase coordination measured as meeting attendance and participation (H. White et al., 2018). The key problem seems to be that while people make the expected contributions, decisions are made by a local elite. This is insufficient to start a virtuous cycle of cooperation for the common good. Ultimately, most CDD projects appear to primarily use the existing social cohesion rather than building it, including in Malawi (Vajja & White, 2008). *A priori*, the same could apply to PWPs.

Most studies of cash transfers demonstrate a positive impact on different outcomes of social cohesion (Attanasio et al., 2015; Barca et al., 2015; Camacho, 2014; Evans et al., 2019; Pavanello et al., 2016; Valli et al., 2019), although a few studies find no effects (Veras Soares et al., 2010) or even unintended negative effects due to perceived unfairness, especially related to targeting (Adato, 2000; Adato & Roopnaraine, 2004; L. Cameron & Shah, 2014; Devereux et al., 2017; Kardan et al., 2010).

Specifically on cooperation for the common good, studies of cash transfer programmes in Peru (Camacho, 2014) and Paraguay (Veras Soares et al., 2010) do not detect effects on coordination, measured by group membership.⁵⁵ However, cash transfer beneficiaries in Columbia are more cooperative in public good games (Attanasio et al., 2015). In Tanzania, beneficiaries report a higher willingness to contribute but actual participation in community work does not increase (Evans et al., 2019). Qualitative evidence from Mexico's conditional cash transfer programme PROGRESA suggests that some non-beneficiaries reduce their contributions because they consider them the task of the beneficiaries (Adato, 2000). In short, there are no strong indications that programmes without a work component commonly result in large changes in coordination or contributions.

⁵⁵ In this paper, we measure coordination through various forms of meeting activities but not through group membership. Yet, in the secondary data that we use, there are also indicators that allow investigating the relationship between public works and group membership. Like the two cited studies we also do not find robust statistically significant effects for group membership. These additional results are available upon request.

However, the work activities of PWPs require close contacts among community members and may stimulate further cooperation outside the framework of the programmes. To our best knowledge, there are only two studies that investigated this. Both find positive effects on horizontal dimensions of social cohesion. Quasi-experimental evidence for India's National Rural Employment Guarantee Act (NREGA) scheme, the largest PWP in the world, suggests that social networks are higher in programme villages (Bhuwania et al., 2016). In a refugee context in Jordan, cash-for-work programme beneficiaries that participate in waste-related public works report a higher willingness to voluntarily cooperate in the waste sector in the future (Loewe et al., 2020).

The implication of the mixed evidence regarding cash transfer programmes and CDD projects and the scarce evidence regarding PWPs is that we cannot derive clear predictions from the literature regarding the expected relationship between PWPs and social cohesion, specifically cooperation for the common good. We anticipate that PWPs can enhance within-community coordination and contributions to local public goods even beyond the framework of the PWP.

4.3 Malawian context and the MASAF PWP

Malawi is a peaceful and politically relatively stable country that made notable improvements in some dimensions of human development in recent years, but poverty and food insecurity remain persistently high. Around half of the population continues to live below the national poverty line (World Bank, 2020). 20.1% lived in extreme poverty in 2016/17, somewhat down from 24.5% in 2010/2011. As a means to bolster the food security of poor households with excess labour capacity, PWPs have been implemented in Malawi since 1996. It has since been the main social protection instrument accessible to the working age population. The PWP under the Malawi Social Action Fund (MASAF) has been by far the longest-running and biggest PWP in the country. Funding for the MASAF PWP comes mainly from the World Bank, but it is implemented through government structures. Phase 3 (2002 to 2015) and Phase 4 (2016 to 2018) of the programme are the main interventions in our analysis.

The MASAF PWP operates nationwide. Funding is allocated to each district in proportion to population size and poverty levels. District officials are then expected to use the same criteria to target specific communities in their districts. Based on findings from other countries (Tavits, 2009), politics can play a role in the geographical targeting of antipoverty programmes, but we have no information whether it does in Malawi. According to the nationally representative Integrated Household Survey data, in 2013 and 2016 70% of the survey clusters were exposed to the PWP. This implies that public works are present in most communities and, therefore, the scope to exert political influence in the geographical targeting is limited.

At the community level, the programme targets the poor and vulnerable with labour capacity. Participants are selected via community-based targeting without clear and standardised procedures and criteria. Officially, the programme foresees wealth rankings that are publicly discussed in community meetings. In practice, the extent of community involvement varies and local traditional leaders (chiefs) often play a key role, sometimes in conjunction with the Village Development Committee (VDC). Access must be rationed because demand usually exceeds the number of spots available in the programme (Beegle et al., 2017). Yet, there are no strict or clear eligibility criteria to guide the rationing, which gives a lot of discretion to local decision making. Studies of the MASAF PWP (Beegle et al., 2017) and other programmes in Malawi with a similar targeting approach (Basurto et al., 2020) find room for improvement in reaching the food insecure and evidence of some nepotism linked to the central role of local leaders in the process, but no signs of severe mistargeting.

Since 2012, the MASAF PWP offers participants up to 48 workdays per year and prior to that only up to twelve workdays (Beegle et al., 2017). The daily wage rate was occasionally adjusted upward to keep up with inflation and varies around the equivalent of somewhat less than 1€ per day. The biggest change from MASAF-3 to MASAF-4 was the shift from selecting participants anew for each work cycle to a three-year targeting period. Hence, predictability of income from the PWP for those selected increased, but those not initially selected could not count on getting access to the PWP within that three-year period. Moreover, the focus of work activities under MASAF-4 shifted

somewhat towards environmental activities such as afforestation and soil and water conservation, but classical infrastructure projects such as road work continued to be undertaken as well.

Several studies, including one experimental study, investigated whether the MASAF PWP achieves its core objectives, in particular, food security (Beegle et al., 2017; Bloom et al., 2005; Chirwa et al., 2002).⁵⁶ To our knowledge, the relationship between the MASAF PWP and social cohesion has not been investigated for any phase.

4.4 Data and methodology

We study the link between PWPs and social cohesion by focusing on within-community cooperation for the common good. Specifically, we anticipate that PWPs can enhance local coordination as well as voluntary contributions to local public goods (outside the framework of the PWP). We investigate these aspects with fixed effects panel data analyses for two different samples. The estimates of a fixed effects panel model rely on within-unit variation whereas between-unit variation is removed. Hence, the coefficients of interest reflect effects for switchers, i.e., units whose public works status has changed over time. Depending on the sample, we estimate the model at the community level (*IHS panel*) or the household level (*M4C panel*).

In the three-period IHS panel, the coefficients of interest show how temporal variation in PWP presence in an enumeration area (EA), i.e., a cluster of communities, is associated with community-level indicators of coordination and contributions to local public goods. We measure coordination through meeting activities, which we separate into vertical meetings (between citizens and local leaders) and horizontal meetings (among citizens). The indicators for contributions are time spent serving on committees, contributions of materials, and other in-kind contributions to community activities. In the two-period M4C panel, the coefficients of interest show the association between change in a household's public works status and its voluntary unpaid labour contributions to

⁵⁶ Notably, employing a randomised controlled trial, Beegle et al. (2017) do not find any evidence that the MASAF-3 PWP improved food security.

community activities (separately from the paid work activities of the PWP). In addition, we disentangle in both samples the sectors where cooperation for the common good takes place.

4.4.1 Secondary data: IHS panel

For the secondary data analysis, we construct an EA-level panel data set from the World Bank's IHS. The IHS tracks the life conditions of Malawian households. It is implemented by the Government of Malawi with the help of the World Bank and International Food Policy Research Institute (IFPRI). Because social cohesion indicators in the IHS data are only available at the EA level, our unit of analysis is an EA. A panel is constructed for EAs interviewed in all three waves (2010, 2013, and 2016). Our preferred sample is a balanced panel of 93 EAs where observation units with missing values for key variables in any wave are removed altogether. Without this restriction, the panel could have a maximum size of 102 EAs and in Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes we show that our results are robust to using the full sample instead.⁵⁷

From the community questionnaire, we extract information on needs that community members have expressed in the last three years, whether any meeting activities to address them took place (villagers approaching local leaders, local leaders organising community meetings, or community members meeting without local leaders), and whether this was successful. Needs are expressed in the following ten sectors: agriculture/livestock, maize mills⁵⁸, schools, health, care⁵⁹, public transportation, roads, bridges, piped water/boreholes, law enforcement, and others. All needs indicate both construction and maintenance/improvement. Although similar indicators of coordination are commonly used as proxies for social cohesion in the literature (as shown in Section 4.2), increased community interactions are not necessarily a sign of increased social cohesion because the need for them may arise from conflicts and dissatisfaction (Gugerty & Kremer, 2008).

⁵⁷ The IHS data samples for every year are much larger but they represent the repeated cross-sectional data. The panel can be constructed only for 102 EAs.

⁵⁸ Cooperation related to maize mills is so rare (see summary statistics in Table B.4.6 of Appendix 4.B: IHS panel, detailed summary statistics for coordination indicators) that estimations for this sector are not meaningful. We therefore exclude it from the sectoral analysis, but it is still reflected in the aggregate variables.

⁵⁹ Health denotes health centre/clinic/dispensary whereas care denotes community-based childcare centres/nursery/orphanages.

Yet, in our setting, the original survey questions (see Appendix 4.A: Survey questions) are phrased such that they mainly seem to capture constructive efforts to address communal needs. In addition, we interpret the somewhat ambiguous outcomes (*approaching village head, organising community members, meetings among community members*) jointly with less ambivalent measures of coordination (*successful actions*). Considering that, according to the survey guidelines, the community questionnaire was answered by ‘a group of several knowledgeable residents’ of the EA, often including the village headmen and other local leaders, there is some risk of misreporting for these questions if they wanted to show themselves in a better light. However, we cannot think of plausible reasons why such misreporting would be more or less probable in communities with PWP presence. Hence, it is unlikely to bias our results.

Information on MASAF PWP coverage is available in the community questionnaire (i.e., for the EA level) and in the household questionnaire. The community-level indicator is a dummy denoting whether the MASAF-4 PWP employs people in the community. Furthermore, we aggregate information about households’ public works status into dummies denoting that there are at least one/two/three PWP participant(s) in an EA, the total number of PWP participants in an EA, and the share of respondents in an EA that report to participate in the PWP.⁶⁰ It must be noted that in the 2010 wave the MASAF PWP in the household questionnaire is combined with other cash for work projects in Malawi.

The set of control variables contains basic community characteristics like rural/urban location, population, number of households, major religions, common marriage types, number of polygamous households, and whether descent is traced through the mother or father.

The descriptive statistics of key variables are summarised in Table 4.1. Initiated meetings, vertically and horizontally, as well as successful actions take place, on average, in around three out

⁶⁰ Note that due to the small number of observations per EA (e.g., 16 in 2010 wave) this share is not representative of the actual PWP coverage in an EA. In principle, there is also community-level information on the share of the population in the community that participates in the PWP ($\frac{1}{4}$, $\frac{1}{2}$ or $\frac{3}{4}$ and more, both for the female and male population). However, we do not use these indicators because their accuracy is questionable considering that data frequently show unrealistically high coverage rates of up to $\frac{3}{4}$ of the population. Irrespective of these concerns over accuracy, the dummy variable for the presence of the MASAF PWP in an EA also has the advantage that it is more likely exogenous than variation in the intensity of coverage.

of four EA-years and approximately two sectors. Voluntary contributions are most frequent in the form of spending time serving in committees, closely followed by providing material inputs and less often other in-kind contributions. Regarding the sectoral composition, vertical or horizontal meeting activities most frequently aim to address needs related to school (50% of the EA-years), closely followed by roads and water. Meeting activities concerning transport/bridges and health were also relatively common (28% and 21%, respectively). In all other sectors, meeting activities took place in not more than 12% of the EA-years.

The MASAF PWP operated in 55% of the EA-years, according to community-level information. The individual-level information suggests the presence of the PWP for a similar share of EA-years, measured by whether at least one respondent in an EA-year reported to be a PWP participant. However, this individual-level measure matches the community level information for only 66% of the EA-years. If the community-level information about PWP presence is not in line with the individual-level information, we regard the former as more reliable because misreporting on this matter by the group that responded to the community questionnaire seems less likely than misreporting by individual households. Therefore, the community-level indicator is our preferred treatment variable in the IHS panel analysis. In Appendix 4.E: Robustness check: Varying the indicator for PWP presence in the IHS panel data analysis, we show that our main results are robust to different ways of dealing with cases where information from the two levels appears to be at odds.

Two third of EAs in the sample are in rural areas. The communities comprise, on average, 7,500 inhabitants in 1,500 households. Community members trace their descent mainly through the mother. The average share of polygamous households is about 7%.

Table 4.1: Descriptive statistics of the IHS data

	Mean	SD	Min	Max
Coordination				
At least one sector				
Approaching a village head (bottom-up)	0.77			
Organising community members (top-down)	0.77			
Meetings among community members (horizontal)	0.72			
Successful actions	0.73			
Number of sectors (10 max)				
Approaching a village head (bottom-up)	2.11	1.88	0	8
Organising community members (top-down)	2.08	1.88	0	8
Meetings among community members (horizontal)	1.84	1.73	0	8
Successful actions	1.76	1.61	0	8
Contributions				
At least one sector				
Time spent serving in committee	0.57			
Material inputs	0.53			
Other in-kind contributions	0.24			
Number of sectors (10 max)				
Time spent serving in committee	1.01	1.10	0	5
Material inputs	0.85	0.99	0	5
Other in-kind contributions	0.35	0.72	0	5
Community meetings (vertical or horizontal) related to [...]				
School	0.50			
Roads	0.47			
Water	0.42			
Transport/bridges	0.28			
Health	0.21			
Care	0.12			
Law	0.11			
Agriculture	0.08			
PWP coverage				
MASAF PWP operates in community (EA-level response)	0.55			
Individual-level responses (aggregated to EA level)				
Number of PWP participants	1.65	2.18	0	10
Share of respondents that participate in PWP	0.10	0.12	0	0.63
At least [...] PWP participant(s)				
One	0.56			
Two	0.39			
Three	0.26			
Four	0.15			
Control variables				
Rural location	0.73			
Total population	7568.71	16755.87	92	200000
Total number of households	1489.39	2819.43	10	35000
Descent traced through father	0.16			
Descent traced through mother	0.64			
Number of polygamous households	105.34	633.36	0	9000

Notes: The reported summary statistics are for the balanced sample where observations with missing values for one or more of the variables of interest are not considered. It comprises 93 EAs and, thus, 279 data points. The main empirical analysis is based on this balanced sample.

4.4.2 Primary data: M4C panel

The two-period M4C panel data were collected from randomly sampled households in three purposely selected village clusters (*catchments* hereafter) where the implementation of the MASAF-4 PWP had started in early 2016. All catchments are located in Malawi's Central Region, one in Mchinji District and the other two in neighbouring Kasungu District. The first wave was conducted in February 2017. In terms of types of public works activities, there were subprojects on afforestation, land management, and irrigation in all catchments, and additionally on roads in two of them.

The decision which households got to participate in the PWP was the outcome of the regular targeting process that took place in late 2015 and was, thus, not randomly assigned. In each catchment, the random sample of households was stratified by PW status, such that half of it comprised households participating in the PWP at the time and the other half of households not participating in the PWP at the time.

The second round took place two years later in the same month to ensure that seasonal variation does not bias the responses. Of the 616 respondents interviewed in the first round, 500 respondents could be re-interviewed. We balance the panel by omitting attrited households from the sample because for our empirical approach that relies on within-unit variation we need observation units that were observed in both waves.

The M4C panel allows us to investigate the relationship between participation in the MASAF-4 PWP and contributions for the common good, specifically voluntary unpaid labour contributions to community works. Note that *community works* in this paper denotes voluntary unpaid collective work outside the framework of the PWP, in contrast to *public works* which denotes remunerated collective work by PWP participants as part of the MASAF PWP. As shown in Table 4.2, we use the total number of workdays across all sectors and six sectoral dependent variables. The unit of these variables are *workdays in the past twelve months*. A workday in the questionnaire was not defined as a certain number of working hours. Instead, respondents were asked to report the number of days on which they contributed some work. We have no reason to believe that the average number of working hours per day substantially and systematically differed by PW status or

location. In the preferred specifications, we winsorise all dependent variables of the M4C panel at fraction 0.98 to avoid distortions by outliers. We show in Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods that the results are robust to winsorising or truncating the dependent variables at different levels/fractions. Table 4.2 also presents descriptive statistics of key household characteristics that serve as control variables in the empirical analysis.

Table 4.2: Descriptive statistics of the M4C data

	Wave 1		Wave 2	
	Non-PW	PW	Non-PW	PW
Voluntary labour contributions to community works				
Number of workdays in last 12 months on [...]				
All sectors combined	5.60 (10.4)	6.62 (12.4)	10.69 (15.5)	13.45 (19.1)
Afforestation	0.05 (0.5)	0.90 (4.5)	0.68 (4.5)	2.03 (7.3)
Land conservation	0.01 (0.2)	0.30 (2.8)	0.25 (2.9)	0.28 (2.8)
Nursery/seedling production	0.00 (0.0)	0.12 (1.8)	0.31 (3.2)	1.62 (6.8)
Road work	0.62 (3.6)	0.58 (3.5)	2.14 (7.1)	2.22 (6.4)
Non-road construction	3.25 (7.3)	2.62 (6.3)	7.57 (13.4)	7.81 (13.9)
School-related activities	2.25 (6.4)	2.49 (7.0)	7.11 (13.4)	7.46 (13.7)
Control variables				
Household size	5.32 (2.3)	5.70 (2.2)	5.23 (2.2)	5.77 (2.1)
Age of household head (in years)	42.20 (15.8)	43.07 (14.7)	43.50 (15.2)	45.29 (14.6)
Married household head	0.80	0.88	0.77	0.87
Maximum education attained by head or spouse				
Primary completed	0.32	0.41	0.32	0.39
Secondary completed or more	0.05	0.10	0.06	0.09
Head or spouse with disability or chronic illness	0.11	0.08	0.28	0.26
Business or wage employment	0.29	0.31	0.26	0.23
Number of 7 productive assets owned	0.92 (1.0)	1.12 (1.1)	1.14 (1.2)	1.42 (1.2)
Number of 14 domestic assets owned	3.46 (2.0)	3.96 (2.2)	3.61 (2.0)	4.41 (2.2)
Number of months with not enough food, last 12 months	3.63 (2.7)	3.83 (3.0)	2.90 (2.6)	2.30 (2.4)
Observations	234	266	218	282

Notes: The reported values are the means with the standard deviation (SD) in parentheses below for non-binary variables. PWP participants are not necessarily the same across waves because some respondents dropped out of the programme and others newly entered between Wave 1 and Wave 2. The sample size of each column group is reported in the last row. The dependent variables are winsorised at fraction 0.98. This corresponds to how the dependent variables are used in the preferred empirical specifications.

4.4.3 Empirical specification

We use a canonical panel data model with fixed effects. Depending on the sample, we estimate that model at the EA level (IHS panel) or at the individual level (M4C panel). The basic econometric specification at the EA level for the IHS panel is as follows:

$$(1) Y_{it} = \alpha + \beta PWP_{it} + \sum \gamma_k X_{it}^k + v_i + \delta_t + \varepsilon_{it},$$

where Y_{it} denotes the respective social cohesion indicator for EA i at period t . PWP_{it} is a dummy whether the MASAF PWP is present in EA i at period t . In other specifications, it denotes which part of the community population participates in PWPs in EA i at period t . The vector of all other control variables X_{it}^k includes rural location, total population and number of households in an EA, descent trace through mother or father, and number of polygamous households. EA fixed effects refer to v_i and capture particular time-constant EA characteristics. Year effects denoted by δ_t capture common shocks and time trends for all EAs. The error term that captures all omitted variables and random errors is ε_{it} . The standard errors are heteroscedasticity-robust and clustered at the EA level.

In the case of the M4C panel, Y_{it} denotes the respective social cohesion indicator for individual i at period t . PWP_{it} is a dummy whether a member of the household is a PWP participant at period t . The vector of all other control variables is X_{it}^k and includes household size, age of household head (plus square term), marriage status, highest education level obtained by head or spouse, disability of head or spouse, quantity of productive and domestic assets owned, employment or business status, and food security. Individual fixed effects refer to v_i and capture particular time-constant individual characteristics. Year effects denoted by δ_t capture common shocks and time trends for all respondents. The error term that captures all omitted variables and random errors is ε_{it} . The reported standard errors are heteroscedasticity-robust but not clustered or bootstrapped because it is not clear whether any alternative would be more accurate. With just three catchments and a moderately high, and widely varying, number of observations per catchment, clustering standard errors at the catchment level is not recommended (C. Cameron & Miller, 2014; Canay et

al., 2017, 2019; MacKinnon & Webb, 2018; Roodman et al., 2019).⁶¹ We show in Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods that the results are robust to using different methods to calculate standard errors, particularly ordinary wild bootstrap.

4.4.4 Potential endogeneity

Combining the results from the two data sources as well as from household and community level analyses cannot fully solve the endogeneity problem. Our empirical strategy therefore allows to observe associations, but we cannot test whether there is a causal effect of public works on social cohesion. The fact that our fixed effects panel analysis does not rely on between-unit variation mitigates endogeneity concerns linked to non-random allocation of the PWP to communities (IHS panel) and non-random selection of PWP participants within communities (M4C panel). Our within-unit estimates could, however, be biased by unobserved factors that affect both PWP status and cooperation for the common good of a given observation unit.

In the IHS panel, the coefficients of interest show how temporal variation in PWP presence is associated with community-level social cohesion outcomes (measured through indicators of coordination and contributions to public goods). As described in Section 4.3, the MASAF PWP is meant to be allocated to communities following pro-poor geographical targeting, but to the best of our knowledge the specific criteria used for this process at the district or sub-district level are unclear. Given that our analysis exploits temporal within-EA variation of PWP presence, the endogeneity concerns regarding between-EA comparisons in a context of pro-poor targeting do not apply. And while we cannot say anything about why a specific EA was covered or not, we can clearly attribute the increase from 22% to 70% in the share of EAs covered between 2010 and 2013 to the nation-wide scale-up of the MASAF PWP in the wake of the large currency devaluation in 2012 (Beegle et al., 2017). This can be regarded as an exogenous shock from the perspective of the specific EAs that benefited from this scale-up. In 2016, the share of EAs covered remained

⁶¹ Clustering at an intermediate level between the household and catchment is not an option either. If PWP subprojects had been allocated to specific villages, we could have clustered at the village level and, thereby, increased the number of clusters. However, there are not enough cases in our sample where the villages and subprojects overlap well enough to consider clustering at the village level as a viable alternative.

close to the 2013 levels, but the PW status of around half of the EAs changed. We have no concrete explanations for this fluctuation. Possible factors may have been a retargeting in the transition from MASAF-3 to MASAF-4, fairness concerns that led to EA-level rotation, (relative) changes in poverty status, or sub-district politics. This knowledge gap also prevents more nuanced considerations regarding endogeneity in the IHS panel analysis.

In the M4C panel, households whose public works status has changed are not necessarily representative of non-switchers. Recall that, contrary to previous MASAF phases, the programme design of MASAF-4 foresees the same households to stay enrolled for three years (spanning from one year before wave 1 until after wave 2). We do not have household-specific information why the public works status changed and, hence, cannot check whether these reasons directly affected voluntary labour contributions. Without this information, we cannot ascertain what it implies for endogeneity. Anecdotal qualitative evidence from the survey catchments indicates that some rotation to share the available spots continued informally, but it is unclear which factors determine who rotates in or out (Beierl & Grimm, 2018).

What are the overall implications of the issues discussed in this section for our empirical approach? The sample-specific endogeneity concerns are so different that it becomes unlikely that the bias would be systematically in the same direction across samples and outcomes, but this might of course just be wishful thinking.

4.5 Results

In this section, we report the results We study the relationship between PWPs and social cohesion by focusing on cooperation for the common good. More specifically, we anticipate that PWPs can enhance coordination, in particular intensify meeting activities, and voluntary contributions to the common good, especially by PWP participants. In the following, the results from the different analyses are presented for these two components.

4.5.1 Coordination

Table 4.3 reports results for coordination from the IHS panel analysis. We report disaggregated results by sector and by dimension of interactions (vertical versus horizontal). The treatment variable is the dummy denoting whether the MASAF PWP operates in an EA. Columns 1 and 2 present top-down and bottom-up interactions between community members and village headman or other local leaders. Column 3 reports the results for horizontal coordination, measured by the initiation of meetings among community members. Column 4 shows whether the meetings were deemed successful in taking the necessary steps to address the needs in the respective sector(s).

The dependent variables in the row for *number of sectors* count *the sectors* (maximum 10) in which YES is reported for the respective social cohesion indicator. We find that all four indicators of social cohesion are higher in the presence of the PWP although only the coefficients for top-down interactions and for meeting success are statistically significant. Top-down interactions take place in 0.67 more sectors than in the absence of the PWP and are successful in 0.65 more sectors.

The dependent variables in the row for *any sector* are dummies denoting whether YES is reported for any of the ten sectors. We do not detect statistically significant effects for any of the four social cohesion indicators, but the average across all EA-years for these indicators is already quite high at around 0.75 (see Table 4.1 in Section 4.4.1).

We find significant positive associations between the presence of the PWP and coordination in three sectors: schools, public transportation/bridges, and to a lesser extent care. The coefficients for the other sectors are also mostly positive but not significant at any conventional level. There is not a single statistically significant negative association. Regarding schools, bottom-up and top-down interactions are higher by 14% and 15%, respectively. Regarding transport/bridges, we find a positive association for both vertical indicators and the horizontal indicator, with effect sizes between 14% and 19%. Regarding care, we find a statistically significant effect for horizontal meetings (9%) but not for vertical meetings.

For all three sectors, the higher meeting activities coincide with positive significant effects for meeting success. Recall that the assessment of meeting success was made by local key informants

who might be the same people that were approached by their community members (bottom-up) or who organised their community members (top-down). Despite this caveat, we take the results for meeting success as consistent with interpreting intensified meeting activities as proxies for higher social cohesion rather than indications of unresolved conflicts or dissatisfaction.

In Appendix 4.E: Robustness check: Varying the indicator for PWP presence in the IHS panel data analysis, we show that these results are robust to varying the indicators for PWP presence in a way that accounts for mismatches between the community-level indicator that we used as our preferred measure and individual-level indicators (Table E.4.10 and Table E.4.11). The results are also robust to using an unbalanced sample where observation points are not removed from the sample if there are missing values for some dependent variables in some years (see Table F.4.14 in Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes).

Our findings contribute to the literature by showing that there are more coordination activities in the form of initiated meeting activities in the presence of the PWP. More specifically, the presence of the PWP is associated with more intensive bottom-up and top-down as well as horizontal interactions on initiating and organising meetings within communities. In addition, we find that the positive association is strong and robust in two specific sectors: school and transport/bridges.

Table 4.3: Main results for vertical and horizontal coordination

	IHS Panel			
	(1) Approaching a local leader (bottom-up)	(2) Leaders organising community (top-down)	(3) Meetings among community members (horizontal)	(4) Meetings successful
All sectors				
Number	0.383 (0.329)	0.670* (0.348)	0.436 (0.333)	0.652** (0.305)
Any	-0.006 (0.070)	0.073 (0.077)	0.059 (0.080)	0.086 (0.072)
Specific sectors				
School	0.144* (0.081)	0.149* (0.080)	0.111 (0.081)	0.183** (0.076)
Road	-0.048 (0.088)	-0.069 (0.089)	-0.131 (0.089)	-0.129 (0.086)
Water	0.032 (0.084)	0.113 (0.092)	0.035 (0.090)	0.106 (0.082)
Transport/bridges	0.139* (0.073)	0.170** (0.074)	0.191*** (0.073)	0.173** (0.073)
Health	-0.015 (0.075)	0.049 (0.072)	0.027 (0.067)	0.082 (0.062)
Care	0.057 (0.060)	0.091 (0.059)	0.095* (0.053)	0.105** (0.051)
Law	0.016 (0.059)	0.065 (0.051)	0.038 (0.053)	0.004 (0.058)
Agriculture	0.055 (0.049)	0.080 (0.050)	0.049 (0.047)	0.061 (0.047)
Treatment variable	PWP in EA	PWP in EA	PWP in EA	PWP in EA
Observation units	93	93	93	93
Observations	279	279	279	279
Waves	2010,2013,2016	2010,2013,2016	2010,2013,2016	2010,2013,2016
EA FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Control variables	YES	YES	YES	YES

Notes: The treatment variable is the dummy for the presence of the MASAF PWP in the EA. For *number*, the dependent variable is the number of sectors in which YES is reported for the respective social cohesion indicator. For *any*, the dependent variable is a dummy for whether YES is reported for any sector. For each specific sector, the dependent variable is a dummy for YES for the respective social cohesion indicator. The control variables are rural location, total population and a number of households in an EA, descent tracing through mother or father, and number of polygamous households. All specifications include EA and time/wave fixed effects. The results are for the balanced sample where observation units with missing values for key variables are excluded altogether. Results for other samples are reported in Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.5.2 Contributions

The results for labour contributions and other in-kind contributions to public goods are summarised in Table 4.4. The first four columns present the results of the EA-level analysis based on the IHS panel where the outcomes are *time* spent on committees, *materials*, and *other in-kind* contributions (columns 2-4) and *any contribution* (column 1) which is the aggregate of the previous three outcomes. For *number* of sectors combined, the dependent variable is the sum of sectors in which the respective contribution was made. For *any* sector, the dependent variable is a dummy denoting whether the respective contribution was made in at least one sector. In the other rows, the dependent variable is the dummy for the respective type of contributions in the respective sector. The treatment variable is the dummy denoting whether the MASAF PWP operates in an EA.

Column 5 presents the results of the household-level analysis based on the M4C panel where voluntary unpaid community work is the outcome. The dependent variables are the *number* of voluntary workdays across all sectors (row 1), a dummy for at least one voluntary workdays in any sector (row 2), and the number of voluntary workdays in the respective sectors. The treatment variable is the dummy denoting whether the household participates in the MASAF PWP.

For all sectors combined, there is a robust positive association between the MASAF PWP and all types of contributions. The results from the IHS panel show that in the presence of the PWP, time on committees is spent in 0.43 additional sectors, materials are contributed in 0.56 additional sectors, and other in-kind contributions are made in 0.27 additional sectors. The results from the M4C panel suggest that when a household is enrolled in the PWP its members contribute 5.7 additional voluntary unpaid workdays. At the extensive margin (row 2), all coefficients of the across-sector dummies are positive but only two are statistically significant. In the presence of the PWP, the occurrence of contributions of materials and any other in-kind contributions is 16% and 14% higher, respectively.

Regarding specific sectors, we find a strong positive association between the MASAF PWP and contributions to the sectors school, transport/bridges, and care. For water and health there is also a positive association albeit somewhat weaker. For the two sectors where we have data from both samples, the results are consistent: There is significant positive association for the school sector

and no significant association for the road sector. Across samples, outcomes, and sectors we do not detect a single statistically significant negative association.

The sectoral results of the M4C panel analysis suggest that when a household is enrolled in the PWP its members contribute an additional 3.6 voluntary unpaid community workdays to school-related building activities, 2.9 workdays to non-road construction (which also comprises school-related construction), and 2.8 workdays to afforestation activities. No significant effects are observed for land conservation and seedling production/nursery (see Table D.4.8 in Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods).

The largest driver of the positive association in the IHS sample analysis are contributions in the form of materials. In the five sectors with significant coefficients the effect size ranges from 6% for health to 17% for school. Regarding the water sector, there is a positive association for material contributions that is significant at the 10% level and none for the other contribution types. Regarding time spent on committees, we only find significant positive associations for transport/bridges (15%) and care (10%). Regarding other in-kind contributions, only the coefficient for the care sector is positive (at the 10% level). Irrespective of the form of contribution, we find no statistically significant associations between the presence of the PWP and contributions for the sectors agriculture, and law (see Appendix 4.E: Robustness check: Varying the indicator for PWP presence in the IHS panel data analysis).⁶²

Because the contributions in the IHS panel are reported at the community level, we do not know whether these results are driven by PWP participants or even non-participants. We also cannot completely rule out that some contributions have directly to do with the public works activities because the IHS questions about voluntary contributions do not specify whether, e.g., unpaid time spent on committees or contributions of materials are directly linked to the MASAF PWP or separate from it. However, we know from the M4C data, where we can disentangle voluntary unpaid labour contributions from public works activities, that the former are often not part and parcel of the latter (Beierl & Grimm, 2018). So, we expect *a priori* that the same holds for the

⁶² In some cases, contributions are so rare that associations with the presence of the PWP cannot be meaningfully estimated.

communities in the IHS sample. There is no information in the IHS data about the sectors in which PWP activities took place in an EA. Of the sectors for which we find positive significant effects, this caveat applies only to transportation/bridges because public works are, in principle, operated in this sector.

The results regarding contributions to public goods based on the IHS panel analysis, like the results regarding coordination, are robust to varying the indicators for PWP presence (see Table E.4.12 and Table E.4.13 in Appendix 4.E: Robustness check: Varying the indicator for PWP presence in the IHS panel data analysis) and to using an unbalanced sample where observation points with missing values for some dependent variables in some years are not removed (see Table F.4.15 in Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes).

The results based on the M4C panel analysis are robust to truncating or winsorising the dependent variables at different levels/fractions, to restricting the sample to households where the same household member responded to the questionnaire in both waves, to not including control variables, and to using different methods to calculate standard errors (see Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods).

The key insight of our findings is that PWPs can be associated with increased contributions to public goods, similar to what has been observed for some CDD projects (e.g. Nguyen & Rieger, 2017). Specifically, we find this positive association both for the presence of a PWP (in the IHS panel analysis) and for individual participation in the PWP (in the M4C panel analysis), we find it for several sectors, especially the school sector, and we find it for different forms of contributions (time, materials, and labour).

Table 4.4: Main results for contributions to local public goods

	IHS Panel				M4C Panel
	(1) Any contribution	(2) Time spent in committee	(3) Materials	(4) Other in-kind contributions	(5) Voluntary community work
All sectors					
Number	1.257*** (0.442)	0.430** (0.215)	0.561*** (0.185)	0.266** (0.130)	5.686** (2.67)
Any	0.097 (0.085)	0.091 (0.087)	0.161** (0.081)	0.137* (0.078)	0.058 (0.081)
Specific sectors					
School	0.165** (0.079)	0.095 (0.077)	0.174** (0.072)	0.098 (0.063)	3.594* (2.001)
Road	-0.026 (0.075)	0.029 (0.066)	0.046 (0.070)	0.020 (0.043)	0.935 (1.024)
Water	0.060 (0.0779)	0.017 (0.0757)	0.125* (0.0637)	0.036 (0.0447)	
Transport/bridges	0.160*** (0.052)	0.149*** (0.052)	0.101** (0.045)	0.024 (0.032)	
Health	0.056* (0.033)	0.047 (0.031)	0.060* (0.031)	-0.002 (0.011)	
Care	0.103** (0.044)	0.098** (0.044)	0.080* (0.041)	0.066* (0.038)	
Afforestation					2.770** (1.174)
Non-road construction					2.926 (2.033)
Treatment variable	PWP in EA				Household in PWP
Unit of analysis	EA				Household
Observation units	93				500
Observations	279				1000
Waves	2010,2013,2016				1, 2
EA FE	YES				NO
Wave FE	YES				YES
Control variables	YES				YES

Notes: Columns 1 to 4 report the results of the IHS panel analysis. The treatment variable is the dummy for the presence of the MASAF PWP in the EA. For *number*, the dependent variable is the number of sectors in which YES is reported for the respective type of contribution. For *any*, the dependent variable is a dummy denoting whether YES is reported for any sector. For each specific sector, the dependent variable is a dummy denoting YES for the respective type of contribution. The control variables are rural location, total population and a number of households in an EA, descent tracing through mother or father, and number of polygamous households. All specifications include EA and time/wave fixed effects. The results are for the balanced sample where observation units with missing values for key variables are excluded altogether. Results for other samples are reported in Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes.

Column 5 reports the results of the M4C panel analysis. The treatment variable is a dummy denoting whether the household is enrolled in the MASAF-4 PWP. For *any*, the dependent variable is a dummy whether a household contributed at least one voluntary community workday in any sector. In the other rows, the unit of the dependent variables are voluntary unpaid community workdays during the previous twelve months. To avoid distortion by outliers, these dependent variables are winsorised at fraction 0.98. The control variables are household size, education levels, age, head or spouse disabled, household head married, sum of productive assets owned, sum of domestic assets owned, employment and business status, and food gap. All specifications include wave fixed effects. The (insignificant) results for the remaining sectors (land conservation and seedling production/nursery) as well as various robustness checks for all sectors are reported in Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods. *Both panels*: *** p<0.01, ** p<0.05, * p<0.1.

4.6 Conclusion

There is an ongoing debate whether and under which conditions social protection fosters social cohesion. Public work programmes are promising for enhancing social cohesion because due to the work component they require a higher quantity and quality of interactions than other types of social protection. Therefore, it is relevant to know more about the relationship between public works programmes and social cohesion. This paper contributes to this literature with evidence on the link between Malawi's MASAF PWP and one attribute of social cohesion, namely cooperation for the common good within communities. The quantitative literature has so far been silent on these issues and there are, to the best of our knowledge, no studies on the African context. To strengthen the robustness of our analysis, we triangulate several independent data sources and various measures of within-community cooperation.

Our empirical analysis shows the positive and significant association between the presence of public work programmes and cooperation for the common good within communities. We demonstrate that the association is robust across specific sectors (especially schools) and along both horizontal and vertical lines. However, we cannot formally test whether this reflects a causal effect of public works on this attribute of social cohesion. Further research is required based on data that is suitable for causal investigation of this relationship.

Another relevant question is whether the presence of PWPs is also associated with improvements in other attributes of social cohesion. Specifically, participation in and satisfaction with the PWP might also improve within-community trust. The presence of the PWP programme could also lead to a more positive perception of the state or government. However, while the MASAF PWP is implemented through the state structures its funding comes mainly from the World Bank. Therefore, it is unclear who people assign praise to.

Investigating the channels through which social protection affects social cohesion is another direction for further research. The potential mechanisms that could affect the relationship are intensified contacts between PWP participants, labour remuneration, benefits from respective public goods, targeting perceptions, and social pressure. Insights into these and other mechanisms

may, for example, help to understand how to avoid unintended negative side effects of social protection programmes on social cohesion in developing countries. Accounting additionally for the perceptions and behaviour of non-participants in the context of social protection programmes would also help to comprehensively uncover the channels linking social protection and social cohesion.

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Appendix

Appendix 4.A: Survey questions

Table A.4.5: Underlying survey questions of the dependent variables

COORDINATION											
IHS, CH1 (Bottom-Top)	Since ..., have any of the community members ever approached the village headman, other village leaders or political leaders about expressing a need for [ITEM] in the community? LIST ITEMS										
IHS, CH2 (Top-Bottom)	Since ..., have the village headman or other village leader or political leaders organised the community members to discuss how to address a need for [ITEM] in the community?										
IHS, CH4 (Horizontal)	Since ..., did the community members (besides village headman and other local/political leaders) meet to find ways to address the need for [ITEM]?										
IHS, CH6 (Success)	Was the meeting(s) successful in determining the steps that were needed to be taken by the community to address the need for [ITEM]?										
CONTRIBUTIONS											
IHS, CH13	To address the need for [ITEM], did the community members: (a) Serve in the project committee? (b) Provide material input such as bricks and sand? (c) Supply any other in-kind contribution?										
MC4	At any time over the last 12 months, did anyone in your household work in a community activity for nothing specific in return?										
MC4	For how many days in total?										
MC4	How many days did you work in [COMMUNITY ACTIVITY] in the last twelve months for nothing specific in return? (1) farming (2) afforestation (3) irrigation (4) land conservation (5) road construction/maintenance (6) fisheries (7) nursery/seedling production ...										
	<table style="width: 100%; border: none;"> <thead> <tr> <th style="text-align: left; width: 50%;">Wave 1</th> <th style="text-align: left; width: 50%;">Wave 2</th> </tr> </thead> <tbody> <tr> <td>Other [SPECIFY]</td> <td>(8) School-related constr. activities</td> </tr> <tr> <td>School</td> <td>(9) School-related non-constr. activities</td> </tr> <tr> <td>Non-road construction</td> <td>(11) Hospital construction</td> </tr> <tr> <td></td> <td>(10) Other activities [SPECIFY]</td> </tr> </tbody> </table>	Wave 1	Wave 2	Other [SPECIFY]	(8) School-related constr. activities	School	(9) School-related non-constr. activities	Non-road construction	(11) Hospital construction		(10) Other activities [SPECIFY]
Wave 1	Wave 2										
Other [SPECIFY]	(8) School-related constr. activities										
School	(9) School-related non-constr. activities										
Non-road construction	(11) Hospital construction										
	(10) Other activities [SPECIFY]										

Notes: [ITEM]s are the following: construction, maintenance, or improvement, respectively, regarding, road, bridge, primary school, secondary school, community-based childcare centres/nursery, health centre/clinic/dispensary, piped water/boreholes/wells, orphanage, maize mill. Initiation/improvement, respectively regarding public transport, law enforcement, agricultural/fishery/livestock extension services; other.

Regarding the M4C data: All regression estimates draw only on the information regarding the twelve months prior to the respective survey wave. Hence, the periods compared are 'Feb 2016 to Feb 2017' (Wave 1) and 'Feb 2018 to Feb 2019' (Wave 2). The intermediate period 'Feb 2017 to Feb 2018' is not considered even though the questionnaire of Wave 2 included additional questions in reference to it. Wave 1 categories 'school' and 'construction' are recoded from string information. Wave 2 categories (8) and (9) are combined to match wave 1 category 'school'. Wave 2 categories (8) and (11) are combined to match wave 1 category 'non-road construction'. Community activities in 'farming', 'irrigation', and 'fisheries' are so rare in the sample that they are not further considered in this paper.

Appendix 4.B: IHS panel, detailed summary statistics for coordination indicators

Table B.4.6: Share of EAs where community meetings took place, by sector, year and PWP presence

	Irrespective of PWP presence					By PWP presence		
	Frequency	Ever	2010	2013	2016	No PWP	With PWP	Diff
School	1.51	0.77	0.47	0.55	0.48	0.52	0.48	0.04
Road	1.42	0.80	0.49	0.43	0.49	0.54	0.42	0.12
Water	1.25	0.77	0.41	0.44	0.40	0.44	0.39	0.05
Transport/bridges	0.83	0.60	0.24	0.27	0.32	0.23	0.31	-0.08
Health	0.62	0.52	0.17	0.17	0.28	0.21	0.21	0.00
Care	0.35	0.33	0.14	0.06	0.15	0.10	0.13	-0.03
Law	0.34	0.30	0.12	0.11	0.12	0.11	0.12	-0.01
Other	0.34	0.31	0.08	0.19	0.08	0.10	0.12	-0.02
Agriculture	0.25	0.24	0.05	0.09	0.11	0.05	0.11	-0.06
Mill	0.13	0.13	0.06	0.04	0.02	0.05	0.04	0.01
Observations	279	93	93	93	93	126	153	

Notes: Community meetings in the context of this table are considered to have taken place if bottom-up, top-down, or horizontal meeting activities are reported in the respective EA-year-sector. PWP presence reflects the community-level indicator denoting whether the MASAF PWP operates in the respective EA-year.

Appendix 4.C: Spatial and temporal EA-level variation of MASAF PWP presence in the IHS panel

Table C.4.7: Spatial and temporal EA-level variation of MASAF PWP presence in the IHS panel

	2010	2013	2016	Ever	Frequency
Northern region	0.18	0.82	0.73	0.82	1.73
Chitipa	0.00	1.00	0.50	1.00	1.50
Karonga	0.00	1.00	1.00	1.00	2.00
Nkhatabay	0.00	1.00	1.00	1.00	2.00
Mzimba	0.00	0.00	0.00	0.00	0.00
Mzuzu City	0.50	1.00	1.00	1.00	2.50
Central region	0.31	0.67	0.69	0.93	1.69
Kasungu	0.00	0.33	0.50	1.00	1.00
Nkhotakota	0.00	1.00	0.50	1.00	1.50
Ntchisi	0.00	1.00	0.00	1.00	1.00
Dowa	0.00	0.80	0.00	0.75	0.85
Salima	0.00	0.00	0.00	0.00	0.00
Lilongwe Rural	0.22	0.86	0.67	0.89	1.76
Mchinji	0.00	1.00	0.00	1.00	1.00
Dedza	0.40	0.25	1.00	1.00	1.64
Ntcheu	0.00	0.25	1.00	1.00	1.25
Lilongwe City	0.75	0.77	1.00	1.00	2.54
Southern region	0.13	0.70	0.78	0.93	1.58
Mangochi	0.00	0.86	0.57	0.86	1.43
Machinga	0.33	1.00	1.00	1.00	2.30
Zomba Rural	0.33	0.33	1.00	1.00	1.67
Chiradzulu	0.00	1.00	1.00	1.00	2.00
Blantyre Rural	0.00	0.00	1.00	1.00	1.00
Mwanza	0.00	0.50	1.00	1.00	1.50
Thyolo	0.00	0.67	0.33	0.67	1.00
Mulanje	0.00	0.67	0.67	1.00	1.56
Phalombe	0.00	1.00	1.00	1.00	2.00
Chikwawa	0.00	0.50	0.50	1.00	1.00
Nsanje	1.00	1.00	1.00	1.00	3.00
Balaka	0.33	0.33	0.67	1.00	1.33
Zomba City	0.33	1.00	1.00	1.00	2.33
Blantyre City	0.00	1.00	0.75	0.75	1.18
Total	0.22	0.70	0.73	0.91	1.65

Appendix 4.D: Robustness check: M4C panel analysis for contributions to public goods

See Table D.4.8 and Table D.4.9.

Table D.4.8: Robustness check: Varying the dependent variables (DV) in the M4C panel data analysis: all sectors combined, afforestation, land conservation, and seedling production/nursery

	All sectors				Afforestation				Land conservation				Nursery/seedling production			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DV winsorised at 0.98	6.099**	5.686**	7.084***	6.657**	2.866**	2.770**	3.014**	2.905**	0.225	0.064	0.240	0.093	0.470	0.371	0.531	0.405
	(2.640)	(2.667)	(2.717)	(2.760)	(1.176)	(1.174)	(1.235)	(1.239)	(0.184)	(0.085)	(0.192)	(0.086)	(0.755)	(0.750)	(0.794)	(0.788)
OWU	0.021	0.027	0.012	0.018	0.010	0.015	0.021	0.029	0.339	0.457	0.364	0.302	0.555	0.689	0.542	0.699
OWR	0.019	0.030	0.013	0.020	0.014	0.015	0.019	0.024	0.310	0.456	0.314	0.304	0.559	0.681	0.543	0.696
DV winsorised at 0.95	4.995**	4.572**	5.897**	5.466**	1.429***	1.308***	1.474***	1.343***	0.235	0.089	0.255	0.108	0.125	0.095	0.137	0.103
	(2.317)	(2.308)	(2.377)	(2.372)	(0.499)	(0.481)	(0.522)	(0.506)	(0.181)	(0.078)	(0.189)	(0.080)	(0.110)	(0.102)	(0.116)	(0.107)
OWU	0.029	0.042	0.016	0.023	0.002	0.004	0.006	0.013	0.349	0.280	0.320	0.214	0.332	0.382	0.336	0.393
OWR	0.026	0.044	0.018	0.025	0.003	0.007	0.006	0.008	0.275	0.278	0.256	0.223	0.306	0.382	0.313	0.397
DV truncated at 100 days	6.783**	6.354**	7.825***	7.376**	3.229**	3.114**	3.433**	3.298**	0.199	0.037	0.217	0.075	0.523	0.337	0.610	0.382
	(2.890)	(2.951)	(2.983)	(3.068)	(1.463)	(1.452)	(1.537)	(1.538)	(0.190)	(0.099)	(0.197)	(0.100)	(1.055)	(1.052)	(1.108)	(1.105)
OWU	0.020	0.031	0.012	0.018	0.023	0.026	0.029	0.039	0.375	0.692	0.385	0.429	0.690	0.838	0.670	0.823
OWR	0.015	0.028	0.011	0.021	0.025	0.034	0.026	0.034	0.368	0.699	0.357	0.441	0.686	0.831	0.672	0.819
DV truncated at 50 days	4.899**	4.472*	5.795**	5.360**	3.270**	3.180**	3.454**	3.350**	0.217	0.055	0.233	0.087	0.584	0.467	0.663	0.515
	(2.293)	(2.281)	(2.352)	(2.343)	(1.463)	(1.457)	(1.538)	(1.540)	(0.186)	(0.089)	(0.193)	(0.090)	(1.056)	(1.052)	(1.109)	(1.105)
OWU	0.031	0.044	0.018	0.024	0.019	0.026	0.027	0.037	0.357	0.529	0.375	0.327	0.634	0.773	0.613	0.759
OWR	0.026	0.047	0.019	0.026	0.022	0.033	0.025	0.034	0.330	0.535	0.334	0.335	0.629	0.756	0.615	0.752
DV: Dummies	0.080	0.058	0.108	0.079	0.120**	0.105**	0.116**	0.099**	0.026	0.011	0.028	0.012	0.031	0.024	0.034	0.026
	(0.081)	(0.081)	(0.084)	(0.084)	(0.049)	(0.047)	(0.051)	(0.048)	(0.018)	(0.008)	(0.019)	(0.008)	(0.027)	(0.025)	(0.029)	(0.027)
OWU	0.343	0.507	0.193	0.354	0.019	0.025	0.036	0.048	0.174	0.204	0.180	0.182	0.333	0.382	0.334	0.396
OWR	0.336	0.503	0.193	0.348	0.019	0.030	0.030	0.047	0.212	0.206	0.210	0.186	0.305	0.380	0.315	0.399
Observation units	500	500	453	453	500	500	453	453	500	500	453	453	500	500	453	453
Observations	1000	1000	906	906	1000	1000	906	906	1000	1000	906	906	1000	1000	906	906
Waves	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2
Control vars	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Wave FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Same respondents	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1; for remaining notes see the following page

Table D.4.9: Robustness check: Varying the dependent variables (DV) in the M4C panel data analysis: roads, non-road construction, and schools

	Roads				Non-road construction				Schools			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Winsorised at 0.98	1.118	0.935	1.217	1.041	2.791	2.926	3.445*	3.508*	3.383*	3.594*	3.781*	3.926*
	(1.054)	(1.024)	(1.103)	(1.079)	(2.020)	(2.033)	(2.081)	(2.096)	(1.980)	(2.001)	(2.066)	(2.097)
OWU	0.286	0.368	0.275	0.334	0.162	0.148	0.104	0.094	0.094	0.082	0.070	0.076
OWR	0.283	0.364	0.281	0.343	0.163	0.149	0.106	0.103	0.093	0.080	0.081	0.075
Winsorised at 0.95	0.503	0.397	0.553	0.452	1.591	1.687	2.124	2.166	2.488*	2.666*	2.786*	2.915**
	(0.423)	(0.409)	(0.443)	(0.429)	(1.482)	(1.477)	(1.515)	(1.502)	(1.375)	(1.372)	(1.432)	(1.434)
OWU	0.254	0.342	0.213	0.294	0.262	0.247	0.160	0.140	0.072	0.059	0.050	0.051
OWR	0.238	0.332	0.216	0.300	0.262	0.245	0.163	0.150	0.070	0.054	0.057	0.049
Truncated at 100 days	2.005	1.775	2.181	1.933	3.608	3.787	4.318*	4.417*	3.899	4.136*	4.337*	4.500*
	(1.758)	(1.724)	(1.843)	(1.814)	(2.309)	(2.364)	(2.387)	(2.457)	(2.374)	(2.444)	(2.480)	(2.571)
OWU	0.257	0.317	0.240	0.293	0.115	0.115	0.070	0.072	0.098	0.092	0.082	0.088
OWR	0.253	0.318	0.251	0.295	0.121	0.112	0.069	0.079	0.095	0.082	0.084	0.087
Truncated at 50 days	1.689	1.458	1.846	1.599	2.838	2.977	3.495*	3.562*	3.404*	3.618*	3.805*	3.952*
	(1.617)	(1.576)	(1.694)	(1.660)	(2.032)	(2.047)	(2.094)	(2.111)	(2.001)	(2.024)	(2.087)	(2.122)
OWU	0.297	0.360	0.272	0.335	0.161	0.145	0.099	0.091	0.094	0.083	0.068	0.076
OWR	0.286	0.360	0.288	0.339	0.160	0.144	0.101	0.101	0.097	0.080	0.081	0.078
DV: Dummies	0.052	0.042	0.059	0.050	0.073	0.064	0.114	0.103	0.105	0.106	0.126*	0.124*
	(0.052)	(0.051)	(0.054)	(0.054)	(0.080)	(0.081)	(0.080)	(0.081)	(0.071)	(0.072)	(0.074)	(0.074)
OWU	0.317	0.407	0.287	0.358	0.382	0.446	0.158	0.214	0.130	0.136	0.098	0.104
OWR	0.318	0.411	0.280	0.374	0.374	0.452	0.153	0.208	0.121	0.126	0.087	0.092
Observation units	500	500	453	453	500	500	453	453	500	500	453	453
Observations	999	999	906	906	1000	1000	906	906	1000	1000	906	906
Waves	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2
Control vars	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Wave FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Same respondents	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Notes: The treatment variable is a dummy for household being enrolled in MASAF-4 PWP. The unit of the truncated/winsorised dependent variables are voluntary unpaid community workdays. Additionally, results for dummies as dependent variables are reported. The control variables are household size, education levels, age, head or spouse disabled, household head married, sum of productive assets owned, sum of domestic assets owned, employment and business status, and food gap. Heteroscedasticity-robust standard errors are in parentheses. Additionally, the p-values calculated with two variants of the ordinary wild bootstrap methods are reported: Unrestricted ordinary wild bootstrap (OWU) and the restricted variant where the null is imposed (OWR). *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.E: Robustness check: Varying the indicator for PWP presence in the IHS panel data analysis

In the preferred specifications reported in the main body of the paper, the treatment variable to capture the presence of the PWP is based on the question from the IHS community questionnaire whether the MASAF operates in the community. However, as noted, there is sometimes a mismatch between this information and whether one or even several individual respondents from a given EA reported to be enrolled in the PWP.

As a robustness check, we exclude observation units from the analysis if there is a mismatch between the community-level information and individual-level information regarding the presence of the PWP in an EA and compare these results to our main results (here referred to as baseline). Specifically, we exclude cases where the EA-level variable states that the MASAF PWP is not present even though more than [1, 2, 3, 4] respondents in that EA report to participate in the PWP. We do not exclude cases where the EA-level variable states that there is no MASAF PWP even though there is no respondent in that EA that reports to participate in the PWP because with only sixteen respondents per EA in 2010 and a few more in later waves it is perfectly possible that by chance no PWP participant was sampled. Table E.4.10 to Table E.4.13 on the subsequent pages show that the main results reported in Section 4.5 are robust to using these alternative indicators of PWP presence instead. Min 4, Min 3, Min 2, and Min 1 refer to using respectively at least four, three, two and one individual respondent who reported to participate in the MASAF PWP as the cut-off threshold for exclusion.

Table E.4.10: Robustness check: Varying the indicator for PWP presence in the IHS panel analysis: vertical coordination

	Approaching a local leader (bottom-up)					Leaders organising community (top-down)				
	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1
Number of sectors	0.3826 (0.3293)	0.2968 (0.3282)	0.5196 (0.3339)	0.5940* (0.3505)	0.7292 (0.5031)	0.6702* (0.3481)	0.5586 (0.3366)	0.9300*** (0.3284)	1.0262*** (0.3544)	1.1612** (0.5305)
Any sector	-0.0055 (0.0696)	-0.0293 (0.0714)	-0.0376 (0.0746)	-0.0094 (0.0733)	0.0213 (0.0987)	0.0733 (0.0769)	0.0412 (0.0778)	0.0820 (0.0857)	0.1289 (0.0855)	0.1870 (0.1320)
School	0.1440* (0.0807)	0.1917** (0.0856)	0.2407** (0.0913)	0.2900*** (0.0995)	0.2902** (0.1314)	0.1491* (0.0795)	0.1771** (0.0826)	0.2615*** (0.0857)	0.3159*** (0.0930)	0.3042** (0.1309)
Road	-0.0478 (0.0875)	-0.0608 (0.0918)	-0.0592 (0.0997)	-0.0456 (0.1082)	-0.0532 (0.1354)	-0.0694 (0.0892)	-0.0852 (0.0920)	-0.0527 (0.1008)	-0.0700 (0.1168)	-0.0793 (0.1348)
Water	0.0316 (0.0838)	-0.0196 (0.0910)	0.0511 (0.0948)	0.0606 (0.0955)	0.0583 (0.1361)	0.1125 (0.0917)	0.0415 (0.0982)	0.1426 (0.0990)	0.1303 (0.0987)	0.1634 (0.1355)
Transport/bridges	0.1393* (0.0729)	0.1722** (0.0796)	0.1822** (0.0891)	0.2020** (0.1006)	0.2263* (0.1303)	0.1701** (0.0739)	0.1578** (0.0786)	0.1593* (0.0885)	0.1733* (0.0978)	0.2137* (0.1258)
Health	-0.0146 (0.0745)	-0.0219 (0.0804)	0.0203 (0.0886)	-0.0151 (0.0843)	-0.0389 (0.1144)	0.0491 (0.0715)	0.0700 (0.0776)	0.1377* (0.0815)	0.0973 (0.0683)	0.0552 (0.0981)
Care	0.0568 (0.0600)	0.0125 (0.0620)	0.0428 (0.0665)	0.0642 (0.0782)	0.0674 (0.0929)	0.0911 (0.0589)	0.0703 (0.0639)	0.1180* (0.0648)	0.1649** (0.0728)	0.2005** (0.0939)
Law	0.0161 (0.0585)	-0.0108 (0.0610)	0.0024 (0.0671)	0.0035 (0.0753)	0.0070 (0.1138)	0.0649 (0.0513)	0.0422 (0.0527)	0.0590 (0.0597)	0.0838 (0.0662)	0.1343 (0.0960)
Agriculture	0.0547 (0.0492)	0.0338 (0.0509)	0.0519 (0.0480)	0.0295 (0.0588)	0.0460 (0.0686)	0.0802 (0.0495)	0.0620 (0.0529)	0.0818* (0.0488)	0.0749 (0.0592)	0.0777 (0.0710)
Observation units	93	84	76	67	51	93	84	76	67	51
Observations	279	252	228	201	153	279	252	228	201	153
Waves			2010, 2013, 2016					2010, 2013, 2016		
EA FE, Wave FE, Control variables			YES					YES		

Table E.4.11: Robustness check: Varying the indicator for PWP presence in the IHS panel analysis: horizontal coordination and meeting success

	Meetings among community members (horizontal)					Meetings successful				
	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1
Number of sectors	0.4360 (0.3331)	0.2377 (0.3035)	0.4113 (0.3066)	0.5409* (0.3188)	0.6732 (0.4790)	0.6517** (0.3050)	0.4697* (0.2624)	0.6868*** (0.2583)	0.5909** (0.2821)	0.7053* (0.3808)
Any sector	0.0589 (0.0802)	0.0260 (0.0815)	0.0420 (0.0917)	0.0953 (0.0951)	0.1547 (0.1317)	0.0861 (0.0716)	0.0618 (0.0725)	0.0973 (0.0787)	0.0974 (0.0903)	0.1326 (0.1135)
School	0.1111 (0.0811)	0.1204 (0.0858)	0.1535 (0.0937)	0.2307** (0.0974)	0.2503** (0.1224)	0.1833** (0.0759)	0.2050** (0.0797)	0.2450*** (0.0854)	0.2492** (0.0955)	0.2379* (0.1215)
Road	-0.1311 (0.0888)	-0.1781* (0.0909)	-0.1808* (0.1002)	-0.1815 (0.1143)	-0.2108 (0.1408)	-0.1287 (0.0864)	-0.1346 (0.0864)	-0.1293 (0.0945)	-0.1457 (0.1100)	-0.2223 (0.1390)
Water	0.0352 (0.0898)	-0.0378 (0.0934)	0.0145 (0.0952)	0.0397 (0.0997)	0.0643 (0.1434)	0.1064 (0.0821)	0.0638 (0.0869)	0.1527* (0.0862)	0.1065 (0.0908)	0.1706 (0.1208)
Transport/bridges	0.1912*** (0.0726)	0.1990*** (0.0749)	0.1940** (0.0825)	0.1998** (0.0932)	0.2070* (0.1191)	0.1729** (0.0732)	0.1590** (0.0749)	0.1603* (0.0815)	0.1416 (0.0957)	0.2032* (0.1168)
Health	0.0269 (0.0674)	0.0248 (0.0695)	0.0591 (0.0733)	0.0370 (0.0662)	-0.0291 (0.0986)	0.0822 (0.0616)	0.0846 (0.0644)	0.1125 (0.0700)	0.0572 (0.0710)	0.0333 (0.1045)
Care	0.0948* (0.0533)	0.0597 (0.0537)	0.0984* (0.0552)	0.1350** (0.0603)	0.1600** (0.0720)	0.1046** (0.0511)	0.0694 (0.0507)	0.1081** (0.0498)	0.1242** (0.0600)	0.1429* (0.0723)
Law	0.0375 (0.0527)	0.0127 (0.0540)	0.0236 (0.0604)	0.0193 (0.0653)	0.0379 (0.0924)	0.0038 (0.0575)	-0.0257 (0.0593)	-0.0162 (0.0655)	-0.0297 (0.0725)	-0.0441 (0.1100)
Agriculture	0.0491 (0.0472)	0.0185 (0.0487)	0.0375 (0.0457)	0.0262 (0.0556)	0.0688 (0.0587)	0.0610 (0.0465)	0.0293 (0.0487)	0.0488 (0.0456)	0.0465 (0.0531)	0.0713 (0.0598)
Observation units	93	84	76	67	51	93	84	76	67	51
Observations	279	252	228	201	153	279	252	228	201	153
Waves	2010, 2013, 2016					2010, 2013, 2016				
EA FE, Wave FE, Control variables	YES					YES				

Table E.4.12: Robustness check: Varying the indicator for PWP presence in the IHS panel analysis: any contributions and contributions of time served in committees

	Contributions: Any					Contributions: Time spent in committee				
	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1
Number of sectors	1.2571*** (0.4422)	1.0922** (0.4409)	1.2271*** (0.4510)	1.2720** (0.4978)	1.9940*** (0.6261)	0.4304** (0.2150)	0.4006* (0.2020)	0.4776** (0.2013)	0.4962** (0.2158)	0.7017** (0.2710)
Any sector	0.0971 (0.0846)	0.0803 (0.0865)	0.1015 (0.0916)	0.1162 (0.1067)	0.1967 (0.1460)	0.0907 (0.0874)	0.0672 (0.0906)	0.0649 (0.0975)	0.1174 (0.1065)	0.1883 (0.1435)
School	0.1654** (0.0792)	0.1712** (0.0853)	0.2215** (0.0887)	0.2219** (0.0998)	0.2573* (0.1296)	0.0946 (0.0773)	0.1285 (0.0814)	0.1616* (0.0851)	0.2132** (0.0978)	0.2471* (0.1235)
Road	-0.0262 (0.0751)	-0.0164 (0.0847)	-0.0264 (0.0865)	0.0139 (0.0900)	0.0943 (0.1057)	0.0293 (0.0659)	0.0526 (0.0726)	0.0431 (0.0739)	0.0934 (0.0729)	0.1132 (0.0973)
Water	0.0595 (0.0779)	0.0363 (0.0784)	0.1045 (0.0806)	0.0331 (0.0922)	0.0702 (0.1215)	0.0168 (0.0757)	-0.0011 (0.0761)	0.0599 (0.0782)	-0.0074 (0.0892)	0.0235 (0.1202)
Transport/bridges	0.1595*** (0.0519)	0.1692*** (0.0554)	0.1614*** (0.0578)	0.1787** (0.0691)	0.2404*** (0.0705)	0.1489*** (0.0517)	0.1543*** (0.0548)	0.1438** (0.0571)	0.1616** (0.0692)	0.2343*** (0.0746)
Health	0.0557* (0.0326)	0.0424 (0.0335)	0.0556 (0.0367)	0.0427 (0.0338)	0.0262 (0.0459)	0.0465 (0.0310)	0.0294 (0.0302)	0.0391 (0.0326)	0.0262 (0.0278)	0.0403 (0.0418)
Care	0.1034** (0.0438)	0.0654 (0.0420)	0.0834 (0.0502)	0.1027* (0.0598)	0.1392** (0.0666)	0.0978** (0.0435)	0.0591 (0.0414)	0.0754 (0.0494)	0.0926 (0.0590)	0.1220* (0.0654)
Law	-0.0281 (0.0454)	-0.0654 (0.0456)	-0.0710 (0.0517)	-0.0835 (0.0530)	-0.1338* (0.0786)	-0.0166 (0.0414)	-0.0538 (0.0403)	-0.0587 (0.0458)	-0.0835 (0.0530)	-0.1338* (0.0786)
Agriculture	0.0008 (0.0153)	-0.0007 (0.0171)	-0.0104 (0.0169)	-0.0241 (0.0190)	-0.0278 (0.0234)	0.0008 (0.0153)	-0.0007 (0.0171)	-0.0104 (0.0169)	-0.0241 (0.0190)	-0.0278 (0.0234)
Observation units	93	84	76	67	51	93	84	76	67	51
Observations	279	252	228	201	153	279	252	228	201	153
Waves		2010, 2013, 2016					2010, 2013, 2016			
EA FE, Wave FE, Control variables		YES					YES			

Table E.4.13: Robustness check: Varying the indicator for PWP presence in the IHS panel analysis: contributions of materials and other in-kind contributions

	Contributions: Materials					Contributions: Other in-kind				
	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1	(1) Baseline	(2) Min 4	(3) Min 3	(4) Min 2	(5) Min 1
Number of sectors	0.5609*** (0.1849)	0.5005*** (0.1844)	0.5788*** (0.1952)	0.5264** (0.2091)	0.8790*** (0.2634)	0.2658** (0.1296)	0.1911 (0.1438)	0.1707 (0.1502)	0.2495 (0.1599)	0.4133** (0.1888)
Any sector	0.1614** (0.0808)	0.1358 (0.0846)	0.1712* (0.0908)	0.1467 (0.1006)	0.3096** (0.1372)	0.1371* (0.0781)	0.0881 (0.0865)	0.0708 (0.0931)	0.1034 (0.1010)	0.2185* (0.1141)
School	0.1741** (0.0716)	0.1571* (0.0798)	0.2061** (0.0823)	0.2267** (0.0919)	0.2718** (0.1107)	0.0982 (0.0629)	0.0892 (0.0717)	0.1070 (0.0722)	0.1258* (0.0747)	0.1203 (0.1014)
Road	0.0457 (0.0701)	0.0314 (0.0770)	-0.0082 (0.0700)	-0.0120 (0.0756)	0.0713 (0.0866)	0.0200 (0.0429)	0.0183 (0.0519)	-0.0252 (0.0273)	-0.0086 (0.0274)	0.0155 (0.0258)
Water	0.1254* (0.0637)	0.1015 (0.0644)	0.1499** (0.0715)	0.0907 (0.0761)	0.2180** (0.1084)	0.0362 (0.0447)	0.0159 (0.0490)	0.0324 (0.0548)	0.0265 (0.0623)	0.1012 (0.0894)
Transport/bridges	0.1010** (0.0446)	0.1248** (0.0504)	0.1152** (0.0536)	0.1122* (0.0630)	0.1387** (0.0637)	0.0235 (0.0321)	0.0327 (0.0360)	0.0209 (0.0354)	0.0173 (0.0436)	0.0672 (0.0442)
Health	0.0597* (0.0307)	0.0517* (0.0294)	0.0694** (0.0308)	0.0534** (0.0261)	0.0524 (0.0390)	-0.0023 (0.0112)	-0.0044 (0.0130)	-0.0059 (0.0153)	-0.0051 (0.0187)	-0.0141 (0.0172)
Care	0.0798* (0.0405)	0.0572 (0.0410)	0.0734 (0.0490)	0.0922 (0.0587)	0.1176* (0.0623)	0.0658* (0.0384)	0.0378 (0.0376)	0.0495 (0.0452)	0.0653 (0.0544)	0.0560 (0.0470)
Law	-0.0221 (0.0270)	-0.0215 (0.0316)	-0.0229 (0.0356)	-0.0453 (0.0384)	-0.0745 (0.0547)	0.0121 (0.0269)	-0.0038 (0.0255)	-0.0037 (0.0290)	0.0207 (0.0214)	0.0251 (0.0265)
Agriculture	-0.0161 (0.0124)	-0.0178 (0.0140)	-0.0195 (0.0157)	-0.0241 (0.0190)	-0.0278 (0.0234)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Observation units	93	84	76	67	51	93	84	76	67	51
Observations	279	252	228	201	153	279	252	228	201	153
Waves			2010, 2013, 2016					2010, 2013, 2016		
EA FE, Wave FE, Control variables			YES					YES		

Appendix 4.F: Robustness check: Using unbalanced IHS panel sample that is not fixed across outcomes

Table F.4.14: Robustness check: Coordination, unbalanced IHS panel

	IHS panel			
	(1) Approaching a local leader (bottom-up)	(2) Leaders organising community (top-down)	(3) Meetings among community members (horizontal)	(4) Meetings successful
Number of sectors	0.3829 (0.3176)	0.6300* (0.3351)	0.3668 (0.3229)	0.6104** (0.2946)
Any sector	-0.0079 (0.0680)	0.0609 (0.0757)	0.0369 (0.0805)	0.0824 (0.0716)
School	0.1231 (0.0781)	0.1392* (0.0777)	0.1006 (0.0792)	0.1825** (0.0734)
Road	-0.0635 (0.0861)	-0.0929 (0.0872)	-0.1467* (0.0866)	-0.1396 (0.0844)
Water	0.0389 (0.0820)	0.1052 (0.0883)	0.0283 (0.0866)	0.1152 (0.0792)
Transport/bridges	0.1476** (0.0721)	0.1681** (0.0710)	0.1872*** (0.0699)	0.1634** (0.0704)
Health	-0.0123 (0.0725)	0.0310 (0.0714)	0.0065 (0.0681)	0.0861 (0.0606)
Care	0.0639 (0.0588)	0.0979* (0.0583)	0.0898* (0.0520)	0.0999** (0.0497)
Law	0.0105 (0.0583)	0.0674 (0.0515)	0.0410 (0.0526)	0.0091 (0.0570)
Agriculture	0.0548 (0.0473)	0.0875* (0.0490)	0.0470 (0.0457)	0.0581 (0.0452)
Observation units	Up to 102	Up to 102	Up to 102	Up to 102
Observations	Up to 299	Up to 299	Up to 299	Up to 299
Waves	2010,2013,2016	2010,2013,2016	2010,2013,2016	2010,2013,2016
EA FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Control variables	YES	YES	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table F.4.15: Robustness check: Contributions to public goods, unbalanced IHS panel

	IHS panel			
	(1) Any contributions	(2) Time spent in committee	(3) Materials	(4) Other in-kind contributions
Number of sectors	1.2140*** (0.4259)	0.3877* (0.2108)	0.5655*** (0.1785)	0.2608** (0.1245)
Any sector	0.0819 (0.0846)	0.0715 (0.0877)	0.1657** (0.0788)	0.1404* (0.0759)
School	0.1635** (0.0765)	0.0890 (0.0748)	0.1764** (0.0694)	0.1085* (0.0612)
Road	-0.0441 (0.0750)	0.0095 (0.0668)	0.0433 (0.0678)	0.0201 (0.0412)
Water	0.0574 (0.0752)	0.0178 (0.0731)	0.1162* (0.0609)	0.0302 (0.0438)
Transport/bridges	0.1494*** (0.0505)	0.1388*** (0.0502)	0.0938** (0.0439)	0.0177 (0.0318)
Health	0.0418 (0.0365)	0.0366 (0.0354)	0.0698** (0.0307)	-0.0029 (0.0151)
Care	0.0993** (0.0426)	0.0943** (0.0423)	0.0777* (0.0395)	0.0633* (0.0371)
Law	-0.0128 (0.0446)	-0.0102 (0.0417)	-0.0107 (0.0273)	0.0111 (0.0263)
Agriculture	0.0004 (0.0149)	0.0004 (0.0149)	-0.0158 (0.0121)	0.0000 (0.0000)
Observation units	Up to 102	Up to 102	Up to 102	Up to 102
Observations	Up to 299	Up to 299	Up to 299	Up to 299
Waves	2010,2013,2016	2010,2013,2016	2010,2013,2016	2010,2013,2016
EA FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Control variables	YES	YES	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1