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Does the geographical footprint of Ethiopia’s flagship social protection programme align with climatic and conflict risks?

August 2023

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Abstract

Ethiopia's flagship 'Productive Safety Net Programme' (PSNP) entered its fifth phase of implementation in 2021. After more than fifteen years, the Government reoriented the programme's targeting of *woreda*s (districts) with a history of food insecurity, to prioritising those experiencing 'extreme poverty through shocks' – particularly drought. In doing so, it has rebranded the PSNP as an 'adaptive' safety net. The focus of the 'adaptive social protection' policy agenda, however, extends beyond responding to biophysical risks associated with climate variability and change; it also seeks to address non-climatic, contextual factors underpinning relational vulnerability to climate change. This study asks whether the PSNP's system of geographic targeting at the start of its fifth phase aligns with this more comprehensive framing of 'adaptive social protection'. Using binary logit regression analysis, it assesses whether the PSNP-covered *woreda*s are those most exposed to three major risks in the country: drought, flooding, and political conflict. We find that, controlling for poverty headcount rate and population density, PSNP coverage is positively associated with districts experiencing higher year-to-year drought conditions, yet *woreda*s with higher multi-year drought variability are less likely to be covered. We find no relationship between PSNP coverage and exposure to flood risk, which is unevenly distributed across the country. Whilst the programme is currently well-targeted toward districts facing disproportionately high levels of political insecurity, this association disappears if the recent escalation of conflict beginning in 2020 is disregarded. As such, this study points to risks that PSNP administrators need to be more attentive to as they consider expanding the programme's geographical footprint to become more 'adaptive'. Doing so could better support the strengthening of PSNP participants' long-term resilience to climate change.

1. Introduction

Ethiopia, with its flagship Productive Safety Net Programme (PSNP), has long been considered a leader on social protection. Now, more than fifteen years since its establishment, as climate change has become a lived reality for its participants, the Government has rebranded it an 'adaptive' safety net: a programme that aims to build the resilience of households living in extreme poverty due to livelihood shocks.

'Adaptive social protection' is a concept that has gained much traction in recent years, among climate and development practitioners and scholars alike. But whilst the policy agenda, as it is developing, has focused overwhelmingly on adjusting social protection programmes like the PSNP to better manage climatic risks with asset transfers, the concept was originally based on a more holistic understanding of what shapes vulnerability. It highlighted the need to understand the specific contexts within which climate hazards occur, which shape why certain segments of the population are more vulnerable to them than others. By also addressing underlying, social and political drivers of vulnerability — such as inequality and marginalisation — adaptive social protection can thus contribute to transforming livelihoods and strengthening people's resilience, in the long-term.

But to what extent does Ethiopia's PSNP reflect this more comprehensive framing of adaptive social protection? This paper approaches this question by focusing on the programme's district-level, geographical alignment with the spatial distributions of drought, flooding and conflict risks. Drought and flooding are the two major biophysical climatic hazards in the country. Proximity to conflict is just one example of a socio-political factor contributing relational vulnerability to climatic change, but one that is crucial to consider given the recent escalation of civil unrest in the country. Using binary logistical regression analysis, we examine how the likelihood of a district being covered by the PSNP changes given its exposure to these different risks.

2. An 'adaptive' PSNP? Case selection, research aims, literature gap

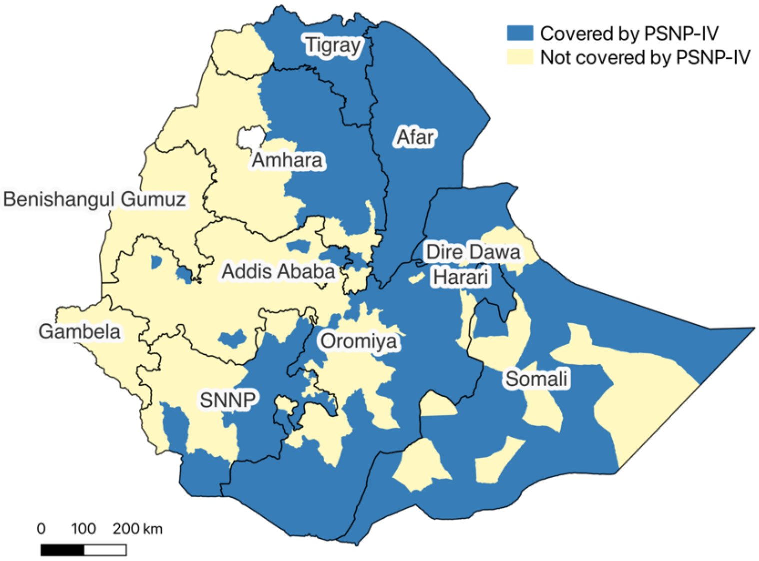
2.1 Ethiopia's Productive Safety Net Programme (PSNP)

The Government of Ethiopia – with support from bilateral and multilateral development partners – launched the PSNP in 2005 in an effort to break away from the cycle of annual emergency aid appeals for addressing the country's widespread and chronic food insecurity (Lavers, 2019; Tenzing and Conway, 2022; The IDL Group, 2008). The programme has since been providing food and/or cash transfers to 2.5 million households in need in select *woreda*s (districts) (World Bank, 2018). While those without labour capacity receive unconditional 'direct support' transfers, approximately 80% of households supported by the PSNP are required to participate in labour-intensive public works in exchange (FDRE, 2020).

The PSNP has evolved since inception, and in 2021, it entered its fifth phase of implementation (PSNP-5). As was done in the past, PSNP-5 builds on lessons from prior phases by making some adjustments to its programming. One such change is a shift in focus from chronic food insecurity to 'extreme poverty through shocks' as its overarching targeting criterion (FDRE, 2020). Up until 2020, the first-stage selection of *woreda* to be covered by the programme was based on food aid allocation data from the previous three years (Berhane et al., 2014; World Bank, 2020)[1]. Figure 1 shows where the PSNP was operating in 2017.

[1] The three-stage process of selecting which households will receive support from the programme following *woreda* identification remains the same: i) the Ministry of Agriculture, in consultation with regional governments, agree on the caseload per *woreda*; ii) *woreda*-level administrators then determine which *kebele* (ward) should be included in the programme; iii) a system of community-based targeting at the *kebele*-level finally identifies which households (if not all) should participate in the programme (Berhane et al., 2014; World Bank, 2020).

Figure 1: *Woreda*s covered by the PSNP in 2017, during its 4th implementation phase (2015-2020). Adapted from UN OCHA (2017).



PSNP-5, however, intends to target *woreda*s (and subsequently, households) that are the most *drought-prone* rather than *food insecure*. Its Programme Implementation Manual (PIM) (FDRE, 2020) says this shift responds to recent analysis by the World Bank (2020), which showed that while food insecurity has fallen rapidly in Ethiopia between 2005 and 2016, extreme poverty for the poorest 10% has deepened in certain regions. Drought may play a role in this situation, but it is complex. For example, the World Bank's Ethiopia Poverty Assessment (World Bank, 2020) reports that in 2016, drought-prone lowlands in Oromiya and the Southern Nationalities, Nations and Peoples (SNNP) region had the highest poverty rate (at 32%). However, this report also notes that drought-prone highlands of Tigray and Amhara had the lowest poverty rates (at 21%) that year, while moisture-reliable highlands (where the population is concentrated) accounted for the bulk of the poor (close to 60%) (World Bank, 2020). This suggests that the PSNP's specific targeting of drought-prone *woreda*s is not entirely consistent with poverty distribution; nevertheless the intention to prioritise responding to drought-related shocks on livelihoods is explicit in PSNP-5.

Related to this, a notable new aspect of PSNP-5 is that it is rebranded an 'adaptive' safety net (FDRE, 2020). While its 'General Programme Implementation Manual' does not define 'adaptive,' one can infer from the growing academic and policy literature on the emerging 'adaptive social protection' agenda why it describes the PSNP as such (Bowen et al., 2020;

Davies et al., 2009; Tenzing, 2020). First, it underlines the overall programme objective as enhancing the resilience of participating households, where 'resilience' is defined as "the ability of households and communities to absorb and recover from shocks, whilst positively adapting and transforming structures and means of living in the face of long-term stresses, change and uncertainty" (FDRE, 2020: 16). Second, it specifies that these shocks can be idiosyncratic, such as sudden loss of income, illness, or crop failure, which typically affect a single household; or covariate, affecting many people simultaneously, as with climate-related shocks – and notably, drought. For such covariate shocks, the PSNP can temporarily scale up its support to protect the consumption and assets of its participants, as well as those who are not regular recipients of transfers, if necessary. Finally, the PSNP's principal feature – its public works component – is said to reduce disaster risk and build longer term community resilience to shocks, particularly climate-related ones through their environmental rehabilitation objectives. As such, the PSNP considers itself to be 'adaptive' because it aims to support vulnerable populations experiencing climatic risk and shocks.

In fact, the PSNP is increasingly regarded to be a model for 'adaptive social protection' in climate change and development policy circles more broadly for these same reasons (Tenzing and Conway, 2022). Some have even hailed it as "Africa's largest climate-resilient programme" (European Commission, 2015). As such, the PSNP experience responding to climate change has important bearing on how the 'adaptive social protection' concept is understood and how this emerging agenda takes shape beyond Ethiopia.

2.2 Addressing biophysical and social drivers of climate vulnerability through 'adaptive social protection'

The 'adaptive social protection' policy agenda is indeed still evolving. However, it has thus far been overwhelmingly concerned with making technocratic adjustments to existing social protection programmes so that they are better able to manage *biophysical* risks associated with climate change, just as the PSNP seeks to do (Tenzing, 2020). Calls for better integration of climate information and early warning systems to determine how much, to whom and when social protection programmes should provide scaled up support when a shock is expected have dominated the literature (Bowen et al., 2020; Daron et al., 2021). This approach certainly has merit, given the impact climate change can have on development progress achieved through social protection (Hallegatte et al., 2016). Conway & Schipper (2011), for instance, show that potential increases in the number of beneficiaries affected by drought under drier climate projections in Africa should prompt the PSNP to address climate risks over the long-term, particularly its financial capacity to absorb additional beneficiaries adversely affected by slow-onset climate change.

Yet, such a framing of 'adaptive social protection' is also limiting, as it perpetuates a narrow interpretation of vulnerability as the result of direct exposure to changing hazards. In other words, it ignores how vulnerability is also shaped by the specific contexts within which these hazards occur (O'Brien et al., 2007; Ribot, 2014, 2011). As critical scholars of climate change and development have long argued, these social, economic and political contexts are what underpin people and societies' *differentiated* capability to anticipate, absorb, and adapt to risks (Bahadur et al., 2015; Eriksen et al., 2021, 2015; O'Brien et al., 2007; Paprocki, 2021; Watts, 2015). Ironically, when they first developed the concept in the late 2000s, Davies et al. (2009) saw 'adaptive social protection' as an opportunity to actively address such underlying drivers of vulnerability to strengthen long-term resilience to climate change. They emphasised its potential to transform livelihoods particularly by redressing structural inequalities and empowering marginalised communities (Arnall et al., 2010). However, this important social dimension of the agenda continues to be overlooked as it develops and begins to be implemented at scale (Béné et al., 2018; Naess et al., 2022; Tenzing, 2020).

2.3 Research aims

This paper examines the extent to which the PSNP aligns with this more comprehensive understanding of 'adaptive social protection'. It assesses how its system of geographical targeting – the first step in the process that determines which households will ultimately be included in the programme – is sensitive to three different risks which rural Ethiopians increasingly face: drought, flood, and conflict. While other safety nets (particularly the Humanitarian Food Aid (HFA) intervention that responds to acute food insecurity) operate in areas not covered by the PSNP (World Bank, 2020), the PSNP is the country's flagship programme, serving 8 million households, and the most institutionalised within government systems. It is also currently the only one with an 'adaptive' objective.

Drought and floods are biophysical hazards that Ethiopia's national climate change policy architecture identifies as posing major threats to the population and economy, particularly its agriculture sector that employs over 80% of the population and contributes 43% of GDP (FDRE, 2015). The World Bank reports that seven million Ethiopians are at risk of food insecurity due to these hazards, with severe drought alone having the potential to shrink farm production by up to 90% (GFDRR, 2019). Droughts in East Africa are reported to have become more frequent, longer and more intense since the early 2000s, and tend to continue across the region's main rainy seasons (Nicholson, 2017; Trisos et al., 2022; Wainwright et al., 2019). At the same time, there is high confidence that intense rainfall and flooding events will increase in frequency under climate change (Niang et al., 2014; Trisos et al., 2022). The most frequent livelihood shock reported by PSNP households corresponds to drought, followed by flooding (Berhane et al., 2013); but whilst targeting drought-prone *woreda*s is a stated objective of the PSNP, the safety net is not explicit in its attention to floods.

Conflict, meanwhile, represents a social risk that has long been present in the country and which has been escalating in recent years. Increasing attention is being paid to the complex connections between conflict and climate change, focusing predominantly on how the latter might contribute to the former (Abrahams and Carr, 2017; Froese and Schilling, 2019; Ide, 2017; Raleigh et al., 2015; Raleigh and Kniveton, 2012; Raleigh and Urdal, 2007; van Weezel, 2020). Yet, the presence of conflict is also a critical determinant of vulnerability to climate change, and often overlooked in climate responses (Abrahams and Carr, 2017; Adger et al., 2014; Intergovernmental Panel for Climate Change, 2022; Naess et al., 2022; Scheffran et al., 2012; Tänzler et al., 2013). The outbreak and persistence of conflict not only affect communities' resilience to shocks and stresses (for example, by causing physical harm or psychological distress, affecting access to resources, critical infrastructure, essential services, or markets, and impacting one's ability to plan for or invest in the future) and increase their support needs; but they also prevent or delay climate action and long-term investment in affected areas (Adger et al., 2014; Eriksen et al., 2021; Naess et al., 2022; O'Brien et al., 2018; Peters et al., 2019).

By focusing on how far PSNP coverage reflects the *woreda*s most exposed to drought, flood and conflict, this study thus takes a first step in assessing how 'adaptive' the safety net is towards two different biophysical risks and one social risk, each contributing to rural populations' vulnerability to climate change. We acknowledge that the consideration of other risks might also be more appropriate. Conflict incidence, for instance, is only one example of a social determinant of vulnerability; and whilst it is a reliable indicator for fragility and security in a given *woreda*, it does not adequately capture social cohesion or marginalisation among the disparate groups within them. Yet, measuring this is difficult. Our aim is that the results and conclusions of this paper form a basis for future evaluations of efforts to implement 'adaptive social protection.'

2.4 Literature review

Numerous studies in the PSNP's lifetime have sought to evaluate its impact, particularly in terms of food security. Early evaluations suggested that the programme had modest effects on the livelihoods of people it supports, due partly to the low level of transfers it had been providing, but a visibly larger impact when combined with complementary services to improve agricultural productivity (hence why the PSNP later incorporated a livelihoods component) (Gilligan et al., 2009; Hoddinott et al., 2012). Some also found that the programme's design was less suited to pastoral livelihoods and therefore it operated less well in dryland regions (Sabates-Wheeler et al., 2013). However, many argued that despite these limitations, the PSNP has succeeded over the years in its primary (and original) objective to prevent famine and reduce chronic food insecurity (Berhane et al., 2014, 2013; Coll-Black et al., 2013). More recent studies are similarly divided. Many remain critical of the PSNP's long-term effectiveness (Adimassu and Kessler, 2015; Azadi et al., 2017; Bahru et al., 2020; Dejene and Cochrane, 2021; Sabates-Wheeler et al., 2021) or the manner in which it can be co-opted for political purposes (Cochrane and Tamiru, 2016; Tenzing and Conway, 2022). Others find that recipients of PSNP transfers do tend be more food secure (including following shocks) than those who are not participating in the programme (Dasgupta and Robinson, 2021; Knippenberg and Hoddinott, 2017; Welteji et al., 2017).

A growing body of literature has also sought to assess the PSNP's contribution to climate action more specifically. Some research finds the ecosystem restoration activities undertaken through its public works component have mitigation co-benefits, and argues that such potential for scaling up nature-based climate action through the PSNP should be further harnessed (Norton et al., 2020; Woolf et al., 2018). Other scholars examine its contribution to adaptation and resilience. They suggest that the PSNP does protect households from adverse effects of climate change in the short term through the provision of well-implemented and regular transfers; however, the safety net has not enabled households to enhance their resilience to climatic shocks and stresses in the long-term, for example by diversifying their livelihoods to productive, non-farm activities (Béné et al., 2012; Duguma, 2019; Ulrichs et al., 2019; Weldegebriel and Prowse, 2013). They therefore underline the importance of complementary interventions to build longer-term resilience to climate risks (Duguma, 2019; Ulrichs et al., 2019). Some studies, however, warn of unintended, maladaptive outcomes arising from PSNP support. Weldegebriel & Prowse (2013) observe an increase in the extraction and sale of natural resources, which they interpret as a negative adaptation strategy that could further increase households' vulnerability in the longer term. Moreover, Mersha & van Laerhoven (2018) find that whilst the creation of community assets through the public works component increases non-PSNP households' capacity to adapt, that of PSNP households is constrained as a result of the labour and time investments the public works require. This is especially true for women, due to both the PSNP's prioritised targeting of female-headed households, as well as local gender norms and power asymmetries.

Although internal conflict in Ethiopia has escalated exponentially in the last two years, in the period between the PSNP's establishment and 2020, the country had generally been enjoying higher levels of political stability compared to its neighbours (Clapham, 2018). It follows that research on how the PSNP operates in or is impacted by fragile contexts is limited. An ongoing UK-funded research programme on 'Better Assistance in Crises (BASIC)' explores the broader question of how social protection can support poor and vulnerable people to cope better with crises (Institute of Development Studies, 2022). Within this body of work, Lind, Sabates-Wheeler, & Szyp (2022) describe how, in Tigray, personnel in charge of PSNP delivery were displaced or left unpaid for months, much of the infrastructure supporting cash payments (such as shops and banks) were shuttered or looted, and markets were no longer able to operate as a result of destroyed roads and bridges and rampant insecurity. As the authors note, this derailment of PSNP operations points to major challenges that social protection systems face because of conflict shocks. In another paper in the series, Naess et al. (2022) consider how insights and approaches to adapting social protection to climate change in politically stable settings (for which the literature is heavily biased towards) are translatable to fragile and conflict-affected ones. They stress that understanding the ways in which political violence, political divisions, attenuated legal and institutional regimes, displacement, the presence of humanitarian actors and the primacy of emergency assistance can shape vulnerability to climate change is critical to the design and delivery of climate-related social protection in fragile settings.

This paper contributes to these areas of research on the PSNP in several ways. It assesses how far its system of geographical targeting aligns with its new 'adaptive' objective. While existing literature on the PSNP's contribution to household climate resilience has focused on drought, this study also considers flooding as the second major and recurrent climate-related covariate shock that Ethiopians face. In addition, it provides a starting point for research on how 'adaptive' the PSNP is in the context of escalating conflict risks, which further contribute to people's vulnerability to climate shocks. Finally, it combines several datasets to offer a unique *woreda*-level analysis of PSNP coverage. We provide further detail about this in the section that follows.

3. Methodology and data sources

As PSNP coverage is a dichotomous variable, we use binary logistical regression (logit) models to assess its association with drought, flooding and conflict risks for each *woreda*, among other variables of interest. PSNP coverage in 2021 is represented by the response variable Y_i where

$$Y_i = \begin{cases} 1 & \text{if woreda } i \text{ is covered by the PSNP} \\ 0 & \text{If woreda } i \text{ is } \textit{not} \text{ covered by the PSNP} \end{cases}$$

The expected value of Y is the probability π that $Y = 1$.

The functional form of the logit model is represented as:

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} = \alpha + \sum_{j=1}^{k} \beta_j X_{ji} \quad (1)$$

where α and β are the unknown parameters of the model to be estimated from our data. X represents a series of k explanatory variables for each woreda i.

The direction of association between explanatory variable X_j and response variable Y_i is reflected in the sign of coefficient β_j. A positive value for β_j shows that X_j increases the probability that $Y_i = 1$, while a negative value for β_j indicates that X_j decreases the probability that $Y_i = 1$.

As such, the logit model also implies the following model for probabilities π (2):

$$\pi_i = \frac{1}{1 + \exp[-(\alpha + \sum_{j=1}^{k} \beta_j X_{ji})]} \tag{2}$$

The results of logit models are typically interpreted in terms of odds ratios (OR). These are obtained by taking the exponential of the estimated coefficients $\hat{\beta}$. We present both estimated coefficients $\hat{\beta}$ and corresponding ORs in our main result tables (Section 4.4). Fitted probabilities calculated from Formula (2) at specific values for X_j help further illustrate the magnitude of the regression effects (Kuha and Lauderdale, 2017).

Finally, we determine which logit models have the best relative fit by performing sequential likelihood ratio (LR) tests on pairs of nested models. Two models are said to be nested when one is constructed by removing variables from the other (Kuha and Lauderdale, 2017). As part of this process, we test each variable X_j in a full, unrestricted model (i.e. using all variables of interest) against the null hypothesis H_0: $\beta_j = 0$ (no association between X_j and Y). Variables are dropped from the model one at a time if we fail to reject the null hypothesis at the 0.05 level of significance. As such, the LR tests also test the model's statistical robustness. Tables reflecting the estimated parameters of both the full and the final (best-fitting) models are presented in the results section of this paper (Section 4, Tables 2 to 4).

In this study, drought exposure, flood risk and conflict incidence are the main explanatory variables we include in the full models. We also include measures for poverty and population density as control variables, given PSNP-5's focus on poverty reduction and on rural areas specifically. We support our interpretation of model results with maps depicting the spatial distribution of our main variables of interest, by *woreda*.

The data we use to conduct this analysis are outlined below.

3.1 Administrative boundaries

The country's first-level administrative boundary is the regional state. There are nine of these – Afar, Amhara, Benishangul Gumuz, Gambela, Harari, Oromiya, Somali, SNNP region, and Tigray – along with two city administrations, Addis Ababa and Dire Dawa. The second-level administrative boundary is the zone, and the third is the *woreda*. It is important to note that Ethiopia's administrative boundaries – particularly at *woreda*-level, are not defined or agreed, and change over time: some *woreda*s split into smaller *woreda*s while others merge. For this study, we obtained administrative boundaries for Ethiopia constructed by the World Bank from various subnational mapping data used for its 2020 Ethiopia Poverty Assessment (World Bank, 2020), among other key analytical projects. These administrative boundaries data – which are not in the public domain – comprise 85 zones and 779 *woreda*s, not counting those within Addis Ababa and Dire Dawa. Our research question and methodology require the use of administrative boundaries to be consistent with PSNP coverage data (detailed in sub-Section 3.3); therefore, all other data we obtained, fitted or constructed for this study are specific to these administrative boundaries. While we plot the spatial distribution of our main variables of interest by *woreda*, the maps in this paper do not explicitly highlight *woreda* boundaries.

3.2 Poverty data

This study uses poverty headcount rates reported by the World Bank for each *woreda*, also used for the 2020 Ethiopia Poverty Assessment (World Bank, 2020). These data come from the 2015/2016 Household Income and Consumption Expenditure Survey, and were calculated using the World Bank's Small Area Estimation methodology (Corral et al., 2020) at the Ethiopian national poverty line[2].

3.3 PSNP coverage

We obtained data on PSNP coverage by *woreda* for 2021 from the World Bank, which leads the coordination team of multilateral and bilateral donors providing funding for the PSNP.

[2] The national poverty line was 7,184 Birr per adult equivalent per year in December 2015 prices (World Bank, 2020).

Currently, these data are not the public domain. Table 1 shows that except for Somali and Dire Dawa, the change in coverage per region from 2017 to 2021 does not exceed 10%. Some of the changes can be explained by PSNP-5's shift in focus from food insecure *woreda*s to those that experience extreme poverty through shocks, particularly drought. They can also reflect changing *woreda* boundaries, i.e. it is possible the *woreda* count has changed despite no actual change in household coverage from PSNP-4 to PSNP-5. 2017's PSNP caseload in Dire Dawa has been taken over by the Urban Productive Safety Net Programme (UPSNP), with the focus of the PSNP remaining on rural households (FDRE, 2020).

The 2017 PSNP coverage map in Figure 1 thus provides a reasonable picture of where the PSNP was operating in 2021 as well. Our analysis is based on PSNP coverage in 2021, the data for which correspond to the administrative boundaries we use.

Table 1: PSNP woreda coverage by region in 2017 (UN OCHA, 2017) and 2021 (World Bank, obtained for this study)

	2017 (PSNP-4)		**2021 (PSNP-5)**	
Region/State	**#**	**%**	**#**	**%**
Afar	32	100	30	91
Amhara	64	50	64	46
Benishangul Gumuz	0	0	0	0
Gambela	0	0	0	0
Harari	1	100	1	100
Oromiya	73	28	70	23
SNNP	79	58	77	52
Somali	32	60	25	37
Tigray	24	71	30	65
Dire Dawa	2	100	0	0
Total	307	44	297	38

3.4 Drought exposure

Peng et al. (2020) offer a high-resolution (5km) Standardised Precipitation-Evapotranspiration Index (SPEI) drought dataset (SPEI-HR) for Africa covering the 35-year period between 1981 to 2016. The SPEI calculation that the authors use was proposed by Vicente-Serrano, Beguería, & López-Moreno (2010) to account for temperature and evaporation effects on drought severity, while retaining the multi-scalar characteristics and simplicity of the Standardised Precipitation Index (Peng et al., 2020). As its name suggests, the SPEI is standardised, with a mean of 0 and a standard deviation of 1. Peng et al. (2020) constructed their SPEI-HR data using daily precipitation data from Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015b) and daily evaporation data from the Global Land Evaporation Amsterdam Model (Martens et al., 2017).

For this study, we compute SPEI-HR values for each of Ethiopia's 779 *woreda*s at 12-month and 36-month timescales, based on the coordinates of their centroids. Different timescales denote different types of drought corresponding to the period water deficits accumulate (Vicente-Serrano et al., 2010a). In this case, we distinguish the experience of year-to-year drought from longer-term, multi-year drought for each *woreda* and assess their effect on PSNP coverage. Regardless of timescale, SPEI values within +/-1 indicate normal conditions, while those below -1 indicate dry conditions (Liu et al., 2021). Using this threshold, for each *woreda*, we calculate the number of dry months from 2005 (when the PSNP was established) to 2016.

3.5 Flood exposure and population density

A study by Rentschler, Salhab, & Jafino (2022) offers high-resolution gridded flood exposure headcount estimates, constructed based on spatial flood and population density maps. This dataset accounts for all flood types relevant for Ethiopia, specifically fluvial flooding (which occurs when intense precipitation causes rivers to overflow) and pluvial flooding (which occurs when precipitation builds up beyond the ground's absorptive capacity). Fluvial and pluvial flood data are based on the 2019 version of Fathom flood hazard data which provide gridded flood depths and extents with a 3-arcsecond resolution (equivalent to 90 by 90-metre grid cells) derived from hydrological and digital elevation models (Sampson et al., 2015; Smith et al., 2015; Yamazaki et al., 2017). The dataset considers floods with a 100-year return period. Population density information is based on the WorldPop Global High Resolution Population dataset (WorldPop, 2022), which provides inhabitant numbers at a 3 arcsecond resolution, based on administrative or census-based population data, disaggregated to grid cells using settlement footprint information from satellite imagery (Freire et al., 2020, 2016). Rentschler et al. (2022)'s gridded flood exposure headcount estimates indicate the number of people per grid cell located in flood zones of different risk levels (i.e., different inundation depths). For this study, we aggregated grid cell level headcounts from Rentschler et al. (2022)'s dataset to the *woreda*-level to estimate *woreda*-level flood exposure.

3.6 Conflict exposure

The Armed Conflict Location & Event Data Project (ACLED) collects reported information on internal political conflict, disaggregated by date, location, and actor since 1997 (Raleigh et al., 2010).[3] The format of the data obtained for this study is event-based, so that each event appears only once. Their location is recorded as specifically as possible: events coded with a spatial precision level of 1 indicate that the coordinates of the town or city where the event is reported to have taken place are known; level 2 indicates that an event is reported to have occurred near a georeferenced town or within second or third-level administrative boundaries for which the coordinates of the capital are used; and level 3 indicates that an event is reported to have taken place in a larger region, for which the coordinates of the closest natural location is used or of the capital of the first-level administrative region if no other information is provided (ACLED, 2019). Events fall into one of six categories: battles, explosions/remote violence, violence against civilians, protests, riots, or strategic developments. 'Strategic developments' typically indicate non-violent but politically important incidents such as arrests, agreements, or non-violent transfer of territory, among others (ACLED, 2019).

From this dataset, we first obtain counts of events which occurred within each of Ethiopia's *woreda* between 1 January 2005 (coinciding with the PSNP's year of establishment) and 31 December 2021, and another set for the period between 1 January 2005 and 31 December 2019 (thus excluding the country's recent escalation of political instability and conflict). For the 2005-21 period, the ACLED reports 6,943 unique incidents[4]: of these only 3.4% have a spatial precision level of 3 (least precise), and 5% are categorised as 'strategic developments.' For the 1997-2019 period, there are 4,481 events[5], of which 4.4% have a spatial precision

[3] The ACLED's sourcing methodology for Ethiopia is available from https://acleddata.com/acleddatanew//wp-content/uploads/dlm_uploads/2021/04/ACLED-EPO_Sourcing-Methodology_April2021.pdf

[4] 21 of these incidents fall outside the national administrative boundaries used for this study.

[5] 8 of these incidents fall outside the national administrative boundaries used for this study.

level of 3 (least precise) and 4.55% are ‘strategic developments.’ Given that they do not constitute a substantial share of the data, we choose to keep observations with spatial precision level of 3 as well as those coded as ‘strategic developments’. Next, we construct new variables for each period, to reflect that households located close to administrative borders can be affected by conflict events occurring in neighbouring areas. For these, we count the number of incidents within a *woreda* plus those occurring within 0.1 degree of its boundaries (equivalent to about 11km), noting that some events will be counted more than once.

3.7 Research and data limitations and alternatives

Spatial analysis constraints: A limitation of this study is that the unavailability or lack of consistency of spatial data constrained the scope of our research questions and methodology. As discussed, Ethiopian administrative boundaries are not fixed, and therefore numerous shapefiles exist reflecting different boundaries for each level. This means that unless available spatial datasets correspond to the same administrative boundaries, they cannot be joined with one another without substantially manipulating the data and compromising the validity of any results. Thus, whilst we have *woreda*-level PSNP coverage data for 2017, we are unable to merge or compare this in a meaningful way with our coverage data for 2021. We have therefore chosen to focus our research question on the more recent, 2021 PSNP coverage dataset because it provides a snapshot of coverage *at the start* of the implementation of PSNP-5, which, unlike previous phases of the programme, has been rebranded as ‘adaptive’ (FDRE, 2020).

Missing food security indicator: Similarly, although we have obtained food security data from the Famine Early Warning Systems Network (FEWS-NET) which has informed PSNP coverage in the programme’s previous implementation phases (FDRE, 2014), these data are aggregated to the zone level and use a shapefile with district-level administrative boundaries that do not match our 2021 PSNP coverage data. This means that, although we can easily assign each *woreda* belonging to a zone its corresponding food security index value, we are unable to do so for the *woreda*s in our shapefile straddling two zones with different values. Taking the average is possible in theory, but as the FEWS-NET food security variable is categorical (i.e. integers between 1 and 5), this solution is imperfect as it renders ‘impossible’ values for many observations. Although we do not include this variable in any of our results tables for this reason, in preliminary analyses, food insecurity is, as expected, a reliable predictor of PSNP coverage by *woreda*.

Drought variable alternatives: With regards to our drought variable, Peng et al. (2020)'s SPEI-HR data give us a choice over various timescales (e.g. 1, 3, 6, 12, 24 or 36 months). As mentioned, different timescales denote different types of drought corresponding to the period water deficits accumulate (Vicente-Serrano et al., 2010a). For this study, we have chosen to use a 12-month timescale to correspond to the experience of year-to-year drought, and a 36-month timescale to reflect longer-term, multi-year drought. Although we can consider SPEI values corresponding to any of the available timescales in our analysis, these longer 1-year and 3-year periods make most sense as indicators of agricultural drought (characterised by low soil moisture), i.e., the primary concern of the PSNP, as a food security-related social protection programme.

A limitation of Peng et al. (2020)'s dataset, however, is that areas that are bare or sparsely vegetated are masked out based on data from the Moderate Resolution Imaging Spectroradiometer land surface type product (MCD12Q1) (Friedl et al., 2010) because – the authors note – SPEI is not reliable over these areas (Peng et al., 2020). This means that 23 *woreda*s (out of 779) have no data, corresponding to dryland areas in Afar (12), Amhara (4), Somali (4) and Oromiya (3). Of these, 11 (48%) are covered by the PSNP. Although we can obtain SPEI values for all *woredas* from an alternative SPEI database – notably SPEI-CRU from the Climatic Research Unit of the University of East Anglia (Beguería et al., 2014, 2010; Vicente-Serrano et al., 2010a, 2010b), our preference is to use the SPEI-HR dataset with missing observations. SPEI-CRU and SPEI-HR are positively correlated (Peng et al., 2020). However, Peng et al. (2020)'s high, 5km spatial resolution SPEI-HR dataset is better suited to district-level analyses (compared to the 0.5 degree ($\approx$ 55km) spatial resolution of SPEI-CRU). Moreover, there are well-established differences between precipitation products covering Africa (Maidment et al., 2015); CHIRPS – from which SPEI-HR is constructed – generally performs well in most parts of the continent, including Ethiopia (Dinku et al., 2018).

Another choice we have made is to use SPEI values corresponding to each *woreda*'s centroid, rather than obtain average values for each *woreda*. A limitation of this is that for a country like Ethiopia with high topographical variation, the centroid's SPEI value might be much higher or lower than at another location within the *woreda*'s boundaries. This risk is higher for *woreda* covering larger areas. Half of the *woredas* in our dataset cover an area of 850 km^2 or less, however, and 75% cover area of 1500 km^2 or less. Only 10% of *woreda*s have an area greater than 3200 km^2, and 5% have an area greater than 5,800 km^2. As such, the risk that centroid SPEI values do not adequately reflect the conditions in the rest of the *woreda* can be considered small.

Highly skewed conflict data: Finally, a limitation of our conflict datasets is that, as expected, they are highly skewed: many *woredas* have experienced little or no conflict events during the 2005-19 and 2005-21 periods, while some have experienced over 200. An alternative to this highly skewed dataset could have been to use an index for conflict and/or fragility. However, obtaining or constructing a robust index proved too difficult given the political sensitivity around making such information publicly available, the uncertainty around the reliability or validity of any input data, and the added challenge of having the index correspond to our study's administrative boundaries.

Ultimately, we chose to minimise the influence of outliers in our dataset without dropping them altogether by winsorising our data at the 99th percentile, i.e. assigning all values above the 99th percentile the value of the percentile itself (Bangalore, 2022; Nyitrai and Virág, 2019). For instance, for the 2005-19 period, the value of the 99th percentile is 77; therefore, all *woreda*s that have experienced more than 77 conflict events are assigned the value 77. For sensitivity testing, we run our logit models with outliers winsorised at the 95th percentile, as well as with their original values.

Sensitivity testing: The outputs of the models we have run using alternative econometric specifications to check on the robustness of our results are reflected in the Appendix. These include:

- **Full logit models with region fixed effects (A1):** these models include the flood risk variable, which is later omitted to obtain the best-fitting models (reflected in Table 4);

- **Logit models that include both drought variables (A2):** while all other logit models in this study include *either* the drought variable using the 12-month timescale *or* the drought variable using the 36-month timescale, these models include *both, together*;
- **Logit models that consider dry *Kiremt* months (Jun-Sep) only (A3):** the drought variables in these models reflect the number of dry months occurring during Ethiopia's primary cultivation season only;
- **Logit models that consider dry *Belg* months (Feb-May) only (A4):** the drought variables in these models reflect the number of dry months occurring during Ethiopia's earlier cultivation season only;
- **Logit models with region fixed effects (A5):** these models include the conflict variable corresponding to the 2005-21 period with region fixed effects, to show that the strength of the association between conflict in the 2005-21 and PSNP coverage becomes stronger when keeping regions fixed;
- **Logit models with conflict variable outliers winsorised at the 95th percentile (A6):** the conflict variable's outliers in these models have been winsorised at the 95th percentile, as opposed to the 99th percentile;
- **Logit models with alternative conflict variables (A7):** the conflict variable's outliers in these models have not been winsorised; moreover, the conflict variable of four of these models reflect conflict events occurring within a 0.1-degree buffer of each *woreda*'s boundaries.

The above models are also referenced within the results and discussion section that follows.

4. Results

We set out to examine how far the PSNP targets *woreda*s most exposed to three major risks in the country: drought, flooding, and political conflict. Accordingly, we developed an initial set of four binary logistical regression analysis models with PSNP coverage in 2021 as the outcome variable (Y), number of dry months (X_1), share of population exposed to flood risk

(X_2) and number of conflict events (X_3) as explanatory variables, and poverty headcount rate (X_4), and population density[6] (X_5) as control variables:

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} \tag{3}$$

The results of these initial models are shown in Table 2. The drought variable (X_1) for models (1) and (2) is based on SPEI values using a 12-month timescale, while for models (3) and (4), it is based on SPEI values using a 36-month timescale. Similarly, the conflict variable (X_3) for models (1) and (3) corresponds to the number of conflict events occurring within 0.1-degree buffers of *woreda* boundaries in the 2005-19 period, while for models (2) and (4), it corresponds to the 2005-21 period. The results of corresponding nested, best-fitting models are shown in Table 3.

We repeated the same analysis with the 2005-19 conflict variable adding region fixed effects to the logit models. Keeping regions fixed, however, restricts our analysis to Amhara, Oromiya, SNNP region, Somali and Tigray (i.e. to 699 *woreda*s instead of 756). Other regions are omitted because the models predict either perfect success (all *woredas* covered by the PSNP) or perfect failure (no *woreda* is covered) for them. The results of the best-fitting models that include region fixed effects (Table 4) therefore serve only to complement the interpretation of those of the main, best-fitting empirical models (in Table 3).

Finally, Table 5 shows the correlation coefficients of all our explanatory variables.

Our overall analysis reflects the following:

i) The probability of PSNP coverage by *woreda* increases with the experience of year-to-year drought (based on SPEI-HR values using a 12-month timescale). However, a *woreda* is less likely to be covered as its experience of multi-year drought (based on SPEI-HR values using a 36-month timescale) increases.

[6] We also controlled for population instead of population density. This generated only marginal differences to our coefficients and associated test statistics, and thus did not alter our overall conclusions.

ii) We find no association between exposure to flood risk and the probability of PSNP coverage. In other words, higher flood exposure does not make a *woreda* more or less likely to be covered by the PSNP.

iii) *Woreda*s with higher conflict incidence between 2005 and 2021 are more likely to be covered by the PSNP. However, we find no association between conflict events and the probability of PSNP coverage if we disregard the recent escalation of conflict beginning in 2020.

iv) In line with its core objectives, the likelihood of PSNP coverage increases as poverty headcount rates rise, and declines as population density increases.

These findings and their implications are discussed in further detail below.

Table 2: Results of full logit models

PSNP coverage (2021)	(1)		(2)		(3)		(4)	
	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**
Poverty headcount rate (%)	0.0339*** *(0.0064)*	1.0344	0.0361*** *(0.0064)*	1.0367	0.0314*** *(0.0063)*	1.0318	0.0336*** *(0.0064)*	1.0342
Population density (per km^2)	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0002)*	0.9996	-0.0004** *(0.0002)*	0.9996
No. dry months (SPEI 12-month timescale)	0.0303*** *(0.0088)*	1.0308	0.0289*** *(0.0088)*	1.0293				
No. dry months (SPEI 36-month timescale)					-0.0126** *(0.0061)*	0.9874	-0.0128** *(0.0061)*	0.9873
Population exposed to flood risk (%)	-0.0050 *(0.0102)*	0.9950	-0.0054 *(0.0103)*	0.9946	-0.0030 *(0.0102)*	0.9970	-0.0034 *(0.0103)*	0.9966
No. conflict events within and close to *woreda* (2005-19)[1]	0.0001 *(0.0031)*	1.0001			0.0009 *(0.0031)*	1.0009		
No. conflict events within and close to *woreda* (2005-21)[1]			0.0066*** *(0.0023)*	1.0066			0.0071*** *(0.0023)*	1.0071
Constant	-1.7412*** *(0.2893)*		-1.9289*** *(0.2945)*		-1.0104*** *(0.2476)*		-1.2213*** *(0.2543)*	
N	756		756		756		756	
Chi-square	60.02***		67.78***		52.20***		61.29***	
Log likelihood	-470.8914		-467.0142		-474.8007		-470.2556	

****p < 0 .01 **p < 0 .05 *p < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

Table 3: Results of best-fitting logit models

PSNP coverage (2021)	(1a)		(2a)		(3a)		(4a)	
	$\widehat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\widehat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\widehat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\widehat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**
Poverty headcount rate (%)	0.0336*** *(0.0063)*	1.0342	0.0359*** *(0.0064)*	1.0365	0.0310*** *(0.0063)*	1.0315	0.0336*** *(0.0064)*	1.0342
Population density (per km^2)	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0002)*	0.9996	-0.0004** *(0.0002)*	0.9996
No. dry months (SPEI 12-month timescale)	0.0302*** *(0.0088)*	1.0307	0.0288*** *(0.0088)*	1.0292				
No. dry months (SPEI 36-month timescale)					-0.0126** *(0.0061)*	0.9875	-0.0129** *(0.0061)*	0.9873
Population exposed to flood risk (%)	omitted		omitted		omitted		omitted	
No. conflict events within and close to *woreda* (2005-19)[1]	omitted				omitted			
No. conflict events within and close to *woreda* (2005-21)[1]			0.0065*** *(0.0023)*	1.0066			0.0071*** *(0.0023)*	1.0071
Constant	-1.7897*** *(0.2652)*		-1.9821*** *(0.2772)*		-1.0214*** *(0.2180)*		-1.2544*** *(0.2337)*	
N	756		756		756		756	
Chi-square	59.77***		67.49***		59.77***		61.18***	
Log likelihood	-471.0146		-467.1555		-474.8909		-470.3102	

****p < 0 .01 **p < 0 .05 *p < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

Table 4: Results of best-fitting logit models with region fixed effects

PSNP coverage (2021)	(1)		(2)		(3)	
	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**	$\hat{\boldsymbol{\beta}}$ $(\widehat{SE})$	**OR**
Poverty headcount rate (%)	0.0377*** *(0.0072)*	1.0384	0.0352*** *(0.0072)*	1.0358	0.0353*** *(0.0072)*	1.0359
Population density (per km^2)	-0.0007*** *(0.0002)*	0.9993	-0.0007*** *(0.0002)*	0.9993	-0.0007*** *(0.0002)*	0.9993
No. dry months (SPEI 12-month timescale)	0.0334*** *(0.0106)*	1.0340				
No. dry months (SPEI 36-month timescale)			-0.0134* *(0.0069)*	0.9867		
No. dry *Belg* months (SPEI 36-month timescale)					-0.0466** *(0.0207)*	0.9545
Population exposed to flood risk (%)	Omitted		Omitted		Omitted	
No. conflict events within and close to *woreda* (2005-19)[1]	0.0116*** *(0.0036)*	1.0117	0.0120*** *(0.0036)*	1.0121	0.0121*** *(0.0036)*	1.0122
Constant	-0.2745 *(0.4642)*		0.4198 *(0.4345)*		0.4373 *(0.4343)*	
Region FE[2]	YES		YES		YES	
N	699		699		699	
Chi-square	141.31***		134.93***		136.27***	
Log likelihood	-392.2244		-395.4101		-394.7414	

****p < 0 .01 **p < 0 .05 *p < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

[2] *Woreda*s in Afar, Benishangul Gumuz, Gambela, Harari, Addis Ababa and Dire Dawa regions are omitted.

Note: See Appendix C.1 for corresponding full models

Table 5: Correlation coefficients of explanatory variables

	Poverty headcount rate (%)	**Population density** (per km^2)	**No. dry months** (12M)	**No. dry months** (36M)	**Population exposed to flood risk** (%)	**No. conflict events** (2005-19)	**No. conflict events** (2005-21)
Poverty headcount rate (%)	1						
Population density (per km^2)	-0.28	1					
No. dry months (SPEI 12-month timescale)	-0.09	0.03	1				
No. dry months (SPEI 36-month timescale)	-0.04	0.02	0.66	1			
Population exposed to flood risk (%)	0.04	0.05	0.04	0.04	1		
No. conflict events (2005-19)	-0.16	0.11	0.07	0.07	0.01	1	
No. conflict events (2005-21)	-0.14	0.10	0.09	0.02	0.01	0.89	1

4.1 PSNP coverage does not align with areas highly susceptible to multi-year drought

Our best-fitting logit models (Table 3) reflect that the odds of a *woreda* being covered by the PSNP multiply by 1.034 (i.e. they increase by 3.4%) with every additional month considered dry using a 12-month SPEI timescale, controlling for poverty headcount rate and population density. Similarly, they increase by 3.7% when also controlling for conflict incidence in the 2005-2021 period. The direction of association between the two variables remains the same when keeping regions fixed as well, with odds of PSNP coverage increasing by 3.4% for every additional dry month (Table 4).

In contrast, however, we find that the likelihood of PSNP coverage is negatively associated with the number of dry months under a 36-month timescale. Controlling for poverty headcount rate and population density, the odds that a *woreda* will be covered by the PSNP decrease by 1.3% with every additional dry month. These results suggest that PSNP-5 is currently well-targeted toward *woreda*s that have experienced higher levels of year-to-year drought between 2005 and 2016, but poorly targeted toward those that have faced greater longer-term, multi-year dry conditions.

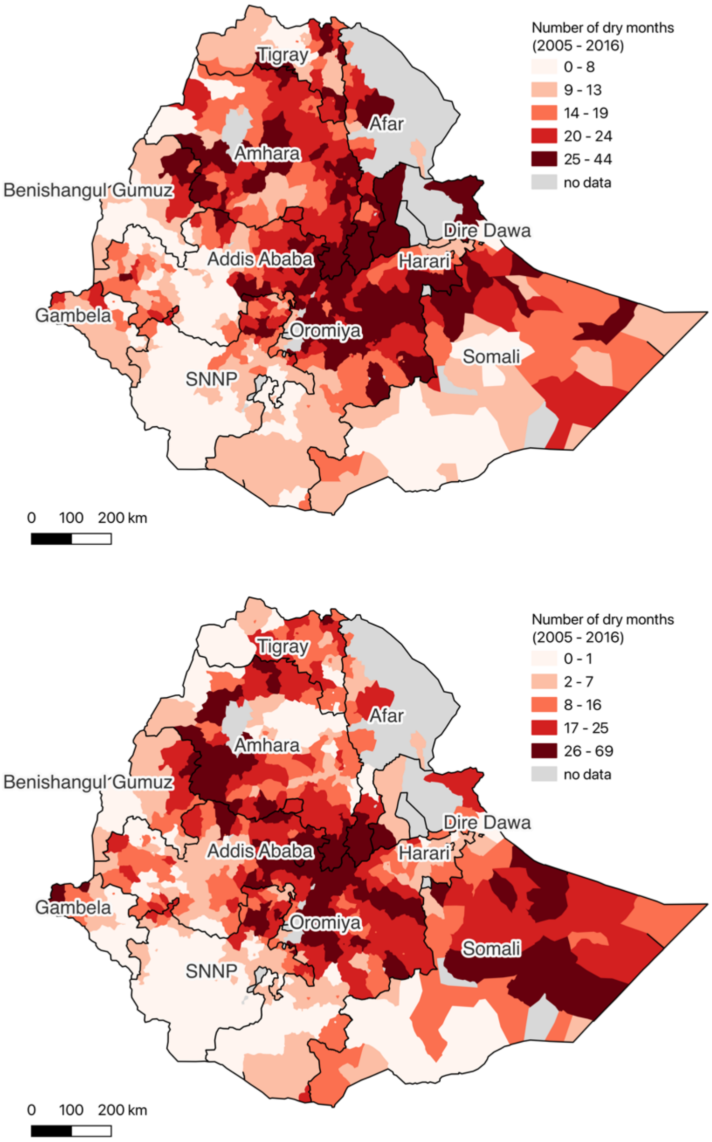
It is helpful to illustrate these results in terms of probabilities. For this, we use the estimated parameters of models (1a) and (3a) in the set of best-fitting logit models (Table 3), holding poverty headcount rate fixed at 0.2608 (the estimated mean) and population density at 162.14 per km^2 (the estimated median). Table 6 shows summary statistics for the two drought variables (which inform the values we choose for fitting probabilities). The estimated probability of PSNP coverage for a *woreda* that has recorded 17 months of dry conditions based on a 12-month SPEI timescale (the estimated median) is 38.8%. Similarly, the likelihood of a *woreda* being included in the programme is 38% if it has 17 recorded dry months based on a 36-month SPEI timescale. There is little difference between year-to-year and multi-year drought experiences in this case. However, *woreda*s that experienced 23, 32 and 39 dry months at a 12-month SPEI-month timescale have a probability of PSNP coverage that is progressively increasing, at 43.1%, 49.9% and 55.2%, respectively, while for those that experienced the same numbers of dry months based on a 36-month timescale, the probabilities are progressively decreasing, at 36.2%, 33.7% and 31.7%, respectively. The estimated probability of PSNP coverage if a *woreda* has recorded 57 dry months based on a 36-month SPEI timescale decreases further to 27%.

Table 6: Number of dry months, by woreda

	No. dry months (12-month SPEI timescale)	No. dry months (36-month SPEI timescale)
Range	0 – 44	0 – 69
Mean	16.71	14.61
Standard deviation	9.09	13.19
Median	17	12
Interquartile range	10 – 23	4 – 22
95th percentile	32	40
99th percentile	39	57
N	757	757

Although the 12-month and 36-month SPEI drought variables are positively correlated, their correlation coefficient of 0.66 reveals that differences between the two remain, leading to these seemingly paradoxical results. The fact that including both variables in a single model strengthens each's association (in their respective direction) with the probability of PSNP coverage is further indication of this (see appendix A2). The contrasting result is because the experience of year-to-year drought and that of multi-year drought have diverging spatial patterns, as reflected in Figure 2 below. The top map captures the distribution of the number of dry months experienced per *woreda* based on SPEI values using a 12-month timescale; the bottom map reflects the spatial distribution of dry months experienced per *woreda* based on a 36-month SPEI timescale. Southern areas of Somali and western parts of Gambela (both low-elevation, dryland regions) stand out as having experienced far greater multi-year drought conditions compared to year-to-year drought over the 2005-16 period, for instance. Conversely, the northern and central highlands of Tigray, Amhara and Oromiya have experienced fewer multi-year drought conditions compared to year-to-year ones.

Figure 2: Spatial distribution of drought by woreda at 12-month (top) and 36-month (bottom) SPEI timescales



Further analysis hints also at seasonal differences between year-to-year drought and multi-year drought. The positive association between PSNP coverage and number of dry months based on a 12-month SPEI timescale strengthens if we only consider those corresponding to the *Kiremt* summer rainfall season (June-September) (see Appendix A3). The odds that a *woreda* is participating in the programme increase by more than 8.4% with every additional dry *Kiremt* month. Similarly, the negative association between PSNP coverage and number of dry months based on a 36-month SPEI timescale strengthens if we only consider those corresponding to the earlier *Belg* spring rainfall season (February-May) (see Appendix A4). In this case, the odds decrease by almost 5% with each additional dry *Belg* month, even when holding region fixed. (Conversely, we find no association that is statistically significant at the

0.05 level between PSNP coverage and dry *Kiremt* months based on a 36-month SPEI timescale, nor between PSNP coverage and dry *Belg* months based on a 12-month SPEI timescale.)

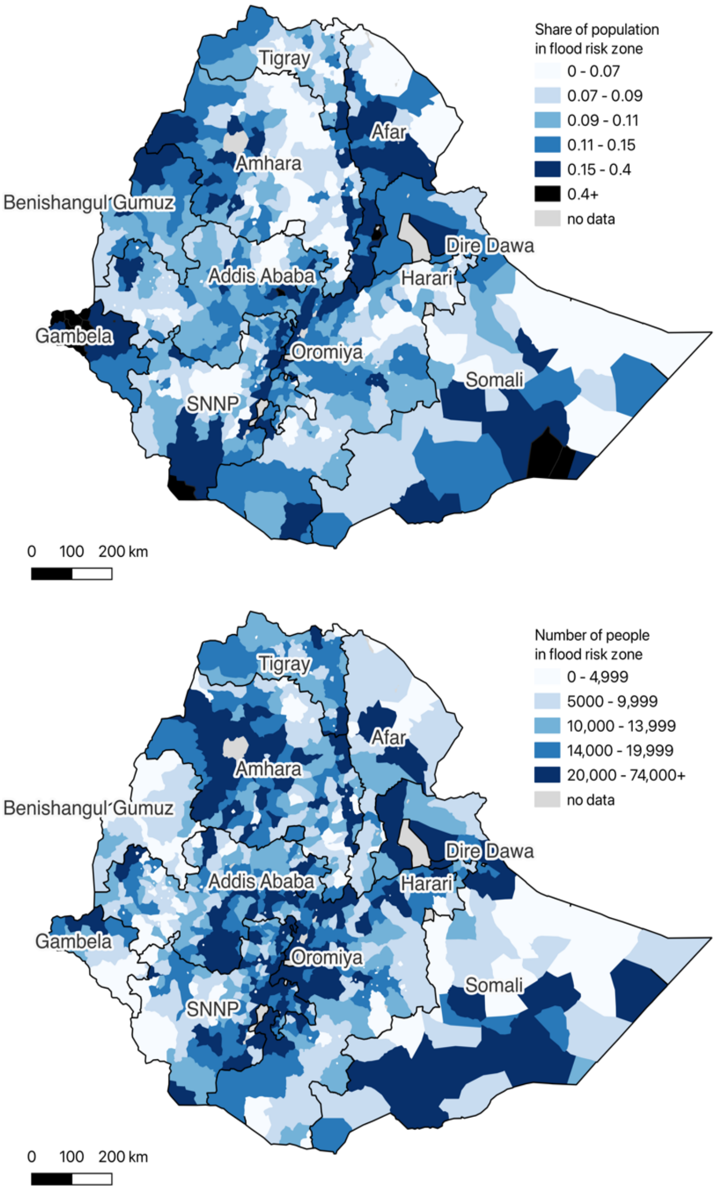
Kiremt summer rains account for 65-95% of total annual rainfall in Ethiopia (Segele and Lamb, 2005; Suryabhagavan, 2017). Occurring in the primary cultivation season (in moisture-rich highland regions especially), they are critically important for the country's agriculturalists, the vast majority of whom are subsistence farmers without access to irrigation (Ehsan et al., 2021; Suryabhagavan, 2017). Historically, the major droughts that are associated with Ethiopia's devastating famines are attributed to a failure of *Kiremt* rains (Suryabhagavan, 2017; Wainwright et al., 2019). In fact, the Government's decision to establish the PSNP in the early 2000s was directly related to the urgent need to prevent future famines— for humanitarian reasons certainly, but also for political ones (Lavers, 2019; Tenzing and Conway, 2022). It is therefore sound, albeit not surprising that the safety net's targeting is particularly responsive to year-to-year drought conditions in *Kiremt* season, which have more immediate and larger scale consequences for food security and people's livelihoods across the country. Yet, earlier *Belg* rains also occur during the cultivation season, and although *Belg* crops have lower yields, these rains are especially important for smallholder farmers and pastoralists in dryland regions (Taffesse et al., 2012). Moreover, whilst *Kiremt* rains record high year-to-year variability (Trisos et al., 2022), a more pronounced drying trend over the Horn of Africa is observed for the *Belg* season (Funk et al., 2015a, 2008; Hoell and Funk, 2014; Liebmann et al., 2014; Lyon, 2014; Rowell et al., 2015; Williams and Funk, 2011; Yang et al., 2014). In Ethiopia, this tendency is stronger over lowlands compared to the northern and central highlands (Suryabhagavan, 2017; Viste et al., 2013).

Overall, these results suggest that whilst PSNP targeting aligns with year-to-year drought exposure affecting the primary agricultural areas of the country, the safety net's comparatively poor presence in those affected by increasing multi-year drought risk contradicts its 'adaptive' objective.

4.2 A woreda's exposure to flood risk currently has no bearing on PSNP coverage

Our data show that approximately 11.1% of the population (more than 11.5 million people) live in high-risk flood zones. This risk is also unevenly distributed across the country, as reflected in Figure 3, with much concentrated along the Great Rift Valley.

Figure 3: Spatial distribution of population exposure to flood risk; top: share of population; bottom: headcount



The top map depicts the share of the population per *woreda* located in flood risk zones, while the bottom map reflects absolute exposure headcount per *woreda*. Despite the magnitude of flood risk over large areas of the country, we find no association between the share of a population exposed in a given *woreda* and its inclusion in the PSNP. (All our best-fitting models therefore exclude the flood risk variable.)

Table 7 reflects regional differences in the number or share of people located in flood risk zones. Estimates of the number of poor people living in these zones are also provided, based on *woreda* poverty headcount rates. Gambela, for instance, has the highest relative share of people exposed to flood risk. However, Oromiya has by far the highest absolute number of people located in flood risk zones, as well as the highest estimated number of exposed people living in poverty.

Table 7: Distribution of flood risk, by region

Region/State	Population	Pop. exposed to flood risk (%)	No. people exposed to flood risk	Poverty headcount rate (%)	No. poor exposed to flood risk
Afar	1,823,000	15.8	314,000	27.8	100,000
Amhara	22,282,000	10.8	2,405,000	24.9	621,000
Benishangul G.	1,136,000	10.8	122,000	24.8	29,000
Gambela	565,000	37.1	209,000	18.6	61,000
Harari	238,000	7.5	18,000	6.2	1,000
Oromiya	39,622,000	10.6	4,215,000	21.8	1,149,000
Somali	6,552,000	13.3	868,000	22.2	204,000
SNNP	21,438,000	11.3	2,422,000	18.0	696,000
Tigray	5,826,000	9.3	543,000	26.9	141,000
Addis Ababa	3,508,000	9.3	328,000	7.3	24,000
Dire Dawa	499,000	14.5	72,000	18.5	13,000

Table 8: Share of population located in flood risk zones, by *woreda* (excluding Addis Ababa and Dire Dawa)

	Pop. exposed to flood risk (%)
Range	0 – 87.78
Mean	11.64
Standard deviation	7.92
Median	9.69
Interquartile range	7.54 – 13.03
95th percentile	25.06
99th percentile	45.61
N	779

At the *woreda*-level, our data moreover show that the average share of the population located in flood risk zones is 11.64 (see Table 8). For 41 *woreda*s, more than 25% of the population is exposed to flood risk. Furthermore, of the 100 *woreda* with the highest share of people living in flood-risk zones, 39 are covered by the PSNP, and of the 100 *woreda*s that have the highest absolute exposure headcount (excluding Addis Ababa and Dire Dawa), 41 are covered. Similarly, of the 100 *woreda*s with the highest estimated number of poor people in flood-risk zones, half are participating in the PSNP, and of the 58 *woreda*s counting more than 10,000 poor people living in flood risk zones, 24 (41.4%) are.

These results illustrate that flood risk exposure is currently an inadequate predictor of PSNP coverage; having a higher share of the population located in flood risk zone does not increase the likelihood that a given *woreda* will be targeted by the programme (though it does not decrease it either). Responding to flood-related shocks is not an explicitly stated objective of the PSNP, nor has it been in past phases of the programme. Yet, the deliberate consideration of the spatial distribution of such a major climatic risk in determining where the safety net should operate could strengthen the PSNP's alignment with its new 'adaptive' objective.

4.3 Although PSNP coverage is currently positively associated with conflict incidence, this was not the case prior to 2019

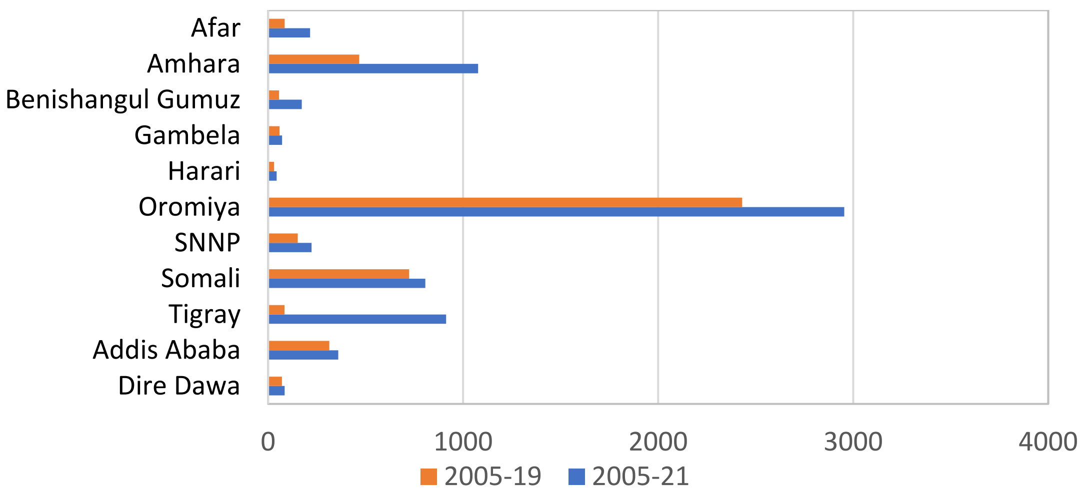
Controlling for poverty headcount rate, population density and drought, we find that the probability that a *woreda* is included in the PSNP increases as conflict incidence in the 2005-21 period also increases. The association between PSNP coverage and the experience of conflict disappears, however, when events that occurred between January 2020 and December 2021 are not considered. Whilst the set of logit models that include region fixed effects do show a positive association between coverage and conflict incidence up until 2019, these results are estimated from data for *woreda*s in Amhara, Oromiya, the SNNP region, Somali, and Tigray only. Holding regions fixed, the odds of PSNP coverage and conflict incidence in the 2005-21 period also become stronger (see Appendix A5).

Table 9 and Figure 4 capture the substantial rise in conflict events reported in Ethiopia since 1 January 2020, by region. Conflict incidence in Tigray in particular has increased by almost 1000%. Prior to 2020, however, most reported conflict events occurred in Oromiya.

Table 9: Number of conflict events, by region

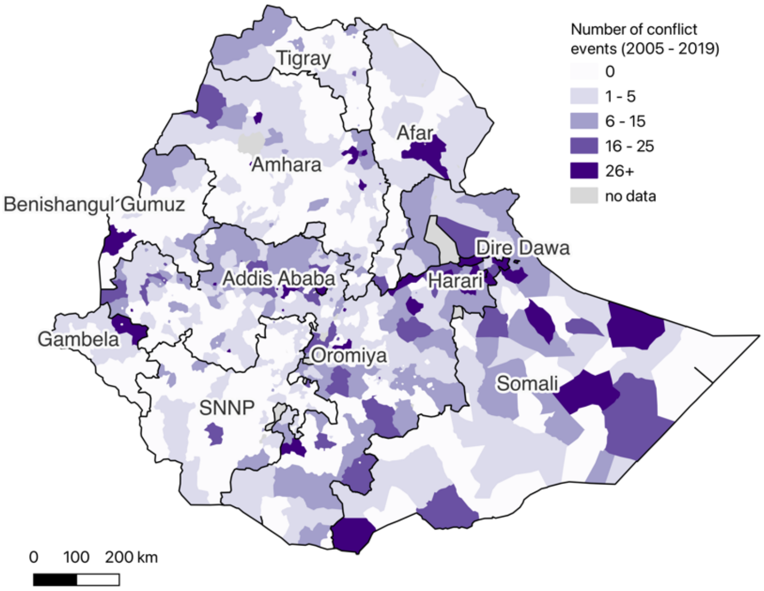
Region/state	2005-19	2005-21	% increase
Afar	85	215	152.9
Amhara	467	1,077	130.6
Benishangul Gumuz	56	173	208.9
Gambela	59	72	22.0
Harari	31	44	41.9
Oromiya	2,431	2,954	21.5
SNNP	152	223	46.7
Somali	723	806	11.5
Tigray	84	913	986.9
Addis Ababa	314	360	14.7
Dire Dawa	71	85	19.7
Total	**4,473**	**6,922**	**54.8**

Figure 4: Conflict incidence, by region



The spatial distribution of conflict by *woreda* for each period is shown in Figure 5, with summary statistics for the two variables – using 0.1-degree buffers and winsorised at the 99th percentile – provided in Table 10. Winsorization at the 99th percentile only alters 7 observations and as such the data remain highly skewed; however, this better captures the magnitude of the difference between *woreda*s at the tail-end experiencing exponentially higher levels of conflict. In comparison, 95% winsorization changes 39 observations and reduces the maximum values to 69 and 90 events for the 2005-19 and 2005-21 periods respectively. Nevertheless, doing so does not affect the direction of the association between conflict incidence and PSNP coverage in any of our models (see Appendix A6).

Figure 5: Spatial distribution of conflict events by *woreda* in the 2005-2019 period (top) and 2005-2021 (bottom) period



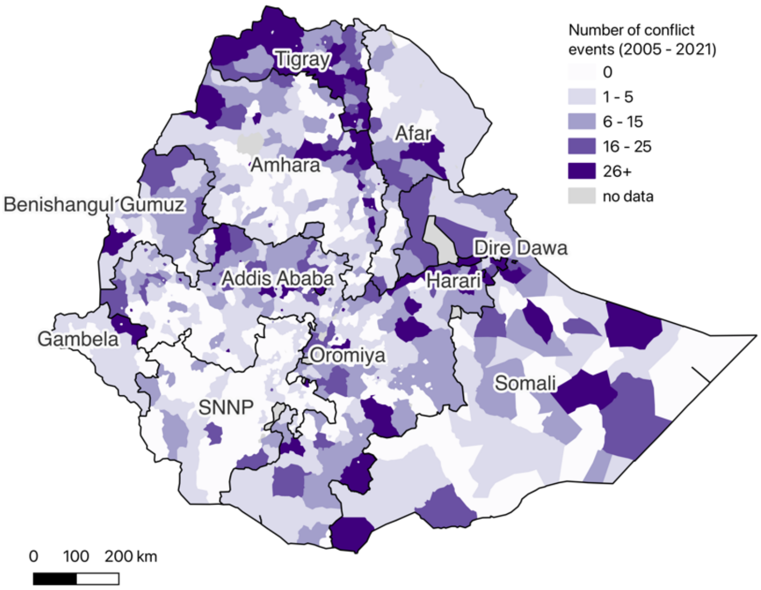


Table 10: Conflict incidence by *woreda*, using 0.1-degree buffers

	2005-19	2005-21
Range*	0 – 155	0 – 180
Mean	17.25	25.34
Standard deviation	27.16	34.07
Median	7	13
Interquartile range	1 – 17	4 - 32
95th percentile	69	90
99th percentile	155	180
N	781	781

Note: **Outliers have been winsorised at the 99th percentile*

Whilst the association between PSNP coverage and conflict incidence between 2005 and 2021 is positive – suggesting that the *woreda*s whose resilience to climatic shocks might be affected by high levels of conflict risk are more likely to be receiving PSNP support than those experiencing less political instability – care must be taken in drawing conclusions from these results. First, in line with the anecdotal evidence described by Lind et al. (2022) – humanitarian actors (e.g. FEWS NET, WFP, & USAID, (2021); UN OCHA, (2022)) report that PSNP operations (in Tigray and Eastern Amhara especially) have been severely disrupted due to the escalation of conflict. As such, *woreda*s with high levels of conflict exposure might be covered by the PSNP in theory, but there is reason to believe support to participating households is interrupted, unreliable or otherwise impacted during these times of fragility and insecurity.

Second, the strength of the association between the two variables is not substantial; controlling for all other explanatory variables, the odds of PSNP coverage increase by only 0.7% with every additional conflict event. This is better reflected with fitted probabilities. Using the estimated parameters of model (2a) in Table 3 (which uses the 12-month SPEI drought variable), we hold population density fixed at 162.14 per km^2, and the other predictors at their mean values. The estimated probability of PSNP coverage for *woreda*s that report no conflict events in the 2005-21 period is 34.8%; for those that have experienced 10, 20, 30 and 40 conflict, the probability increases in small increments to 36.3%, 37.8%, 39.4%, and 40.9%, respectively. It is only for the 1% of *woreda*s reporting very large numbers of conflict events – 180 or more – that the probability of PSNP coverage is much higher, at 63.4%. Yet, the experience of 30 or 40 conflict incidents over a 17-year period is certainly not negligible and can affect communities' resilience to climatic (and other) shocks.

Finally, as we find no association between PSNP coverage and conflict incidence in the 2005-19 period, we have reason to confirm that decisions on where to target the safety net in 2021 were not informed by conflict risk. While recognising that all our models can only point to association (and not causation), we believe the relatively good coverage of very high conflict-affected *woreda*s is more likely to be a legacy of the past 15 years of PSNP operations. Indeed, considering its size relative to other regions, the safety net has consistently had wide presence and performed well in Tigray especially (Berhane et al., 2013; Sabates-Wheeler et al., 2021). As noted in previous scholarship, decisions regarding the PSNP – including its establishment and geographical targeting – have been and still are deeply political (Cochrane and Tamiru, 2016; Lavers, 2019; Tenzing and Conway, 2022). The catastrophic famine that occurred between 1983 and 1985 disproportionately affected northern Ethiopia, and were triggered not only by shortfalls of *Kiremt* rains as already mentioned, but also civil unrest; in fact, it played a direct role in toppling the previous military regime in 1991 (*ibid*). Addressing chronic food insecurity in these parts of the country was a priority for the newly established Federal Democratic Republic of Ethiopia, whose first elected Prime Minister, Meles Zenawi, was himself from Tigray (Lavers, 2019; Tenzing and Conway, 2022; The IDL Group, 2008).

Ultimately, our results point to the need for stronger (or more deliberate) PSNP coverage over *woreda*s affected by conflict, which not only shapes but also exacerbates many rural Ethiopians' vulnerability to climatic shocks. This said, there are many challenges to (and yet limited experience in) designing and providing 'adaptive' social protection in fragile and conflict-affected settings, as Naess et al. (2022) outline. Indeed, targeting that aligns with well with the spatial distribution of conflict risks – as is currently the case for the PSNP – proves fruitless if these obstacles are not fully understood and addressed first.

4.4 The likelihood of PSNP coverage increases with lower population density and higher levels of poverty

Finally, the estimated coefficients for our control variables – population density and poverty headcount rate – is consistent with the PSNP's focus on rural areas and core objective to reduce extreme poverty. Summary statistics for both variables are listed in Tables 11 and 12. Across all our models in Table 3, we find that (holding other variables constant) the odds of PSNP coverage decrease by 0.04% as population density increases by 1 person per km^2. The strength of the association might seem low, but fitted probabilities illustrate that this figure is not unsubstantial. Using the parameters of model 1(a) in Table 3 and holding all other variables constant at their mean values, we estimate that a *woreda* with a population density of 162.14 per km^2 has a 38.6% chance of being covered by the PSNP. The probability of coverage decreases to 37.5% for *woreda*s with a population density of 285.15 per km^2. It declines to 25.4% and even further to 6.9% for those with a population density of 1862.37 per km^2 and 6109.26 per km^2. We infer from these results that the safety net's effectively targets rural areas where population is less concentrated over small areas.

Table 11: Population density, by *woreda*

	Population density (per km^2)
Range	2.08 – 10776.73
Mean	425.55
Standard deviation	1010.11
Median	162.14
Interquartile range	67.42 – 285.15
95th percentile	1862.37
99th percentile	6109.36
N	781

Conversely, the association between PSNP coverage by *woreda* and poverty is positive. We find that (holding other variables constant), the odds of coverage increase by between 3.2% and 3.7% with every percentage point increase in the poverty headcount rate. Holding population density fixed at the median value of 162.14 km^2 and number of dry days (based on a 12-month SPEI timescale) at the mean value of 16.72, the estimated probability of PSNP coverage for a *woreda* with the median poverty headcount rate of 0.248, for instance, is 31.7% (based on model (1a) in Table 3). For *woreda*s with poverty headcount rates of 0.333, 0.506 and 0.637, the probabilities increase to 44.5%, 58.9% and 69% respectively. PSNP coverage by *woreda* thus aligns well with the spatial distribution of poverty in Ethiopia.

Table 12: Poverty headcount rate, by *woreda*

	Poverty headcount rate (%)
Range	0.45 – 78.02
Mean	26.08
Standard deviation	13.14
Median	24.83
Interquartile range	17.06 – 33.34
95th percentile	50.62
99th percentile	63.72
N	779

People's capability to absorb, cope with and recover from shocks is certainly closely linked to their level of poverty (Hallegatte et al., 2016; Jafino et al., 2020), and as such, the positive association between poverty and the likelihood of PSNP coverage is promising. This said, we find little correlation between poverty and each of our drought, flooding and conflict variables (see Table 5). As such, it cannot be assumed that by virtue of the PSNP's targeting of rural *woreda*s according to poverty rates, those at risk of drought, flooding and/or conflict will receive support. In fact, in its recent poverty assessment for the country, the World Bank (2020) found that this first-stage selection of *woreda*s adds little to household targeting performance of the PSNP, and suggested a re-think on the merits of geographical targeting, given the relatively small disparities in welfare among rural *woreda*s. Our study concludes that since PSNP-5 has chosen to retain geographical targeting, moving forward it needs to be better informed by the spatial distribution of different climatic and social risks – such as multi-year drought, flooding and conflict risks – in line with its intention to be an 'adaptive' safety net.

5. Discussion and conclusion

This paper has sought to assess the extent to which the 'adaptive' PSNP's current system of geographic targeting aligns with three major risks rural Ethiopians face: drought, flooding, and conflict. We find that the likelihood of PSNP coverage increases as the experience of year-to-year drought increases, particularly if a *woreda* is recording dry conditions during the key summer cultivation season. Paradoxically, however, the probability of coverage falls as the experience of multi-year drought rises; this is especially true for parts of the country over which a declining trend in spring rainfall is observed – notably in the lowlands, where livelihoods are more reliant on this earlier season. We furthermore find no association between PSNP coverage and exposure to flood risk. This result is not surprising, given that responding to flood-related shocks is not an explicitly stated objective of PSNP-V nor was it at the time of the PSNP's establishment. However, the new data generated and presented in this study shows that this major climatic risk is unevenly distributed across the country. As for conflict, whilst we find that the PSNP is currently well-targeted toward districts facing disproportionately high levels of political insecurity, these results should be treated with caution. Indeed, this association disappears if we disregard the recent escalation of conflict in Tigray and neighbouring areas, suggesting that these *woreda*s were not deliberately targeted because of conflict.

Several broader conclusions can be drawn from these findings about the future of the 'adaptive' PSNP. For instance, this study shows that the safety net is still privileging the areas that it has covered since its establishment. The failure of summer rains (corresponding to year-to-year drought) have long been connected to the country's history of devastating famines (Suryabhagavan, 2017; Wainwright et al., 2019). In fact, finding a solution to decades of recurrent famines is precisely what motivated the Ethiopian Government to establish the safety net in the early 2000s. The political urgency to deliver on the promise of food security continues to underpin policy narratives and decisions today, including around how the safety net should be made 'climate-smart' or 'adaptive' (Tenzing and Conway, 2022). It is undoubtedly also politically difficult or economically illogical to cease PSNP operations in the places where people have come to depend on the programme or where the institutional capacity for implementation already exists.

It is by no means unreasonable that PSNP targeting should be responsive to a form of drought risk that has immediate and large-scale consequences for food security and people's livelihoods across the country. Yet, this study's finding that there is a *negative* relationship between PSNP coverage and multi-year drought risk, affecting different areas and populations of the country (i.e., lowland regions and pastoral communities), shows that the programme's consideration of what constitutes drought risk is limited. This is problematic especially because prioritising drought response is an explicitly stated objective of the PSNP (unlike the other risks considered in this paper). As these areas observe more pronounced drying trends, expanding PSNP-5 coverage accordingly is imperative. Doing so would also align with recommendations of past evaluations of the safety net for more tailored PSNP intervention for pastoral livelihoods in dryland regions (Sabates-Wheeler et al., 2013).

This study's findings that flood risk and conflict risk are poor predictors of PSNP coverage, on the other hand, do not necessarily translate to a recommendation for PSNP-5 *should* be more responsive to them. Indeed, it is important to acknowledge that PSNP resources are finite, and there will be a continued need for Government to make difficult choices over which areas or households to support, and how much support to provide. The aim of this research was to test the PSNP's alignment to a yet undefined 'adaptive' objective, and in particular highlight the importance of taking into account contextual drivers of vulnerability to climate change in doing so, such as exposure to conflict. The consideration of other types of risk could have been more appropriate. Conflict incidence, in particular, is only one example of a social risk; and whilst it is a reliable indicator for fragility and security in a given *woreda*; it does not capture social cohesion or marginalisation among the disparate groups within them, which are critical determinants of contextual vulnerability to climate change.

Moreover, although the PSNP is Ethiopia's *flagship* social protection programme, other safety nets do operate in the country which might have better coverage over the areas highly exposed to the risks considered in this paper. In fact, the Government-managed Humanitarian Food Aid (HFA) operation – though, as its name suggests, is concerned with providing humanitarian assistance (related to acute food insecurity) rather than social protection – intentionally targets rural areas where the PSNP is not active (World Bank, 2020). In a recent study, Sabates-Wheeler, Hirvonen, Lind, & Hoddinott (2022) have found that the ability of these two programmes deliver a continuum of support in response to different types of vulnerability and risk is indeed promising. They also note that the ongoing conflict in Ethiopia and its disruptive effect on PSNP operations highlight the importance of the harmonisation of historically siloed humanitarian and social protection sectors. However, humanitarian responses are typically short-term and often characterised by one-off payments, while social protection constitutes more regular support (Béné et al., 2018; Sabates-Wheeler et al., 2022). As such, further research is also needed to assess how responsive other social protection programmes operating in Ethiopia are not only to biophysical climate risks (such as those considered in this paper) but also to contextual drivers of vulnerability to climate change, and whether they complement the PSNP in delivering transformative, 'adaptive' social protection.

Appendices

A1. Results of full logit models with region fixed effects

The following table reflects coefficients of the full models with region fixed effects; the corresponding nested models are reflected in Table 6.4 (Section 6.4).

PSNP coverage (2021)	(1) $\hat{\beta}$ ($\widehat{SE}$)	(2) $\hat{\beta}$ ($\widehat{SE}$)	(3) $\hat{\beta}$ ($\widehat{SE}$)
Poverty headcount rate (%)	0.0378*** *(0.0072)*	0.0352*** *(0.0072)*	0.0353*** *(0.0072)*
Population density	-0.0007*** *(0.0002)*	-0.0007*** *(0.0002)*	-0.0007*** *(0.0002)*
No. dry months (SPEI 12-month timescale)	0.0335*** *(0.0106)*		
No. dry months (SPEI 36-month timescale)		-0.0134* *(0.0069)*	
No. dry *Belg* months (SPEI 36-month timescale)			-0.0466** *(0.0207)*
Population exposed to flood risk (%)	-0.0025 *(0.0155)*	0.0011 *(0.0158)*	0.0010 *(0.0158)*
No. conflict events within and close to *woreda* (2005-19)	0.0116*** *(0.0036)*	0.0120*** *(0.0036)*	0.0121*** *(0.0036)*
Constant	-0.2544 *(0.4812)*	0.4104 *(0.4548)*	0.4287 *(0.4548)*
Region FE[2]	YES	YES	YES
N	699	699	699
Chi-square	141.33***	134.94***	136.28***
Log likelihood	-392.2118	-395.4076	-394.7393

****p* < 0 .01 ***p* < 0 .05 **p* < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

[2] *Woreda*s in Afar, Benishangul Gumuz, Gambela, Harari, Addis Ababa and Dire Dawa regions are omitted.

A2. Results of logit models that include both drought variables

The following table reflects coefficients of the models that include both drought variables (Section 6.4.1).

PSNP coverage (2021)	(1)		(2)	
	$\widehat{\beta}$ $(\widehat{SE})$	OR	$\widehat{\beta}$ $(\widehat{SE})$	OR
Poverty headcount rate (%)	0.0362*** *(0.0064)*	1.0369	0.0381*** *(0.0065)*	1.0358
Population density	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0002)*	0.9993
No. dry months (SPEI 12-month timescale)	0.0786*** *(0.0124)*	1.0817	0.0763*** *(0.0125)*	1.0793
No. dry months (SPEI 36-month timescale)	-0.0494*** *(0.0086)*	0.9518	-0.0486*** *(0.0087)*	0.9867
Population exposed to flood risk (%)	Omitted		Omitted	
No. conflict events within and close to *woreda* (2005-19)[1]	Omitted			
No. conflict events within and close to *woreda* (2005-21)[1]			0.0060** *(0.0024)*	
Constant	-1.9665*** *(0.2730)*		-2.1371*** *(0.2843)*	
N	756		756	
Chi-square	95.61***		101.68***	
Log likelihood	-453.0949		-450.0617	

****p* < 0.01 ***p* < 0.05 **p* < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

A3. Results of logit models that consider dry *Kiremt* months only

The following table reflects coefficients of the models that consider the number of dry months occurring in the *Kiremt* season only (Section 6.4.1).

PSNP coverage (2021)	**(1)** $\hat{\beta}$ $(\widehat{SE})$	**(1)** OR	**(2)** $\hat{\beta}$ $(\widehat{SE})$	**(2)** OR	**(3)** $\hat{\beta}$ $(\widehat{SE})$	**(3)** OR	**(4)** $\hat{\beta}$ $(\widehat{SE})$	**(4)** OR
Poverty headcount rate (%)	0.0343*** *(0.0064)*	1.0349	0.0366*** *(0.0064)*	1.0372	0.0312*** *(0.0063)*	1.0317	0.0335*** *(0.0064)*	1.0340
Population density	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0002)*	0.9996	-0.0004** *(0.0002)*	0.9996
No. dry *Kiremt* months (SPEI 12-month timescale)	0.0813*** *(0.0245)*	1.0847	0.0777*** *(0.0246)*	1.0880				
No. dry *Kiremt* months (SPEI 36-month timescale)					-0.0309* *(0.0264)*	0.9695	-0.0318* *(0.0165)*	0.9687
Population exposed to flood risk (%)	-0.0059 *(0.0102)*	0.9941	-0.0063 *(0.0103)*	0.9937	-0.0031 *(0.0102)*	0.9969	-0.0034 *(0.0103)*	0.9966
No. conflict events within and close to *woreda* (2005-19)	-0.0001 *(0.0031)*	0.9999			0.0008 *(0.0031)*	1.0008		
No. conflict events within and close to *woreda* (2005-21)[1]			0.0066*** *(0.0023)*	1.0066			0.0071*** *(0.0023)*	1.0071
Constant	-1.6634*** *(0.2797)*		-1.8608*** *(0.2860)*		-1.0359*** *(0.2460)*		-1.2484*** *(0.2523)*	
N	756		756		756		756	
Chi-square	59.03***		66.93***		51.40***		60.55***	
Log likelihood	-471.3859		-467.4385		-475.2036		-470.6259	

****p* < 0.01 ***p* < 0.05 **p* < 0.1*

[1] Top-end outliers winsorized at 99th percentile.

A4. Results of logit models that consider dry *Belg* months only

The following table reflects coefficients of the models that consider the number of dry months occurring in the *Belg* season only (Section 6.4.1).

PSNP coverage (2021)	(1)		(2)		(3)		(4)	
	$\hat{\beta}$ $(\widehat{SE})$	OR	$\hat{\beta}$ $(\widehat{SE})$	OR	$\hat{\beta}$ $(\widehat{SE})$	OR	$\hat{\beta}$ $(\widehat{SE})$	OR
Poverty headcount rate (%)	0.0322*** *(0.0063)*	1.0328	0.0345*** *(0.0064)*	1.0351	0.0315*** *(0.0063)*	1.0320	0.0337*** *(0.0064)*	1.0343
Population density	-0.0004** *(0.0002)*	0.9996	-0.0004** *(0.0001)*	0.9996	-0.0004** *(0.0002)*	0.9996	-0.0004** *(0.0002)*	0.9996
No. dry *Belg* months (SPEI 12-month timescale)	0.0402 *(0.0256)*	1.0401	0.0369 *(0.0258)*	1.0375				
No. dry *Belg* months (SPEI 36-month timescale)					-0.0498*** *(0.0186)*	0.9514	-0.0494*** *(0.0187)*	0.9518
Population exposed to flood risk (%)	-0.0040 *(0.0102)*	0.9960	-0.0045 *(0.0103)*	0.9955	-0.0029 *(0.0102)*	0.9971	-0.0033 *(0.0103)*	0.9967
No. conflict events within and close to *woreda* (2005-19)[1]	0.0004 *(0.0031)*	1.0004			0.0011 *(0.0031)*	1.0011		
No. conflict events within and close to *woreda* (2005-21)[1]			0.0069*** *(0.0023)*	1.0069			0.0070*** *(0.0023)*	1.0070
Constant	-1.4230*** *(0.2817)*		-1.6200*** *(0.2872)*		-0.9498*** *(0.2491)*	0.3868	-1.1607*** *(0.2561)*	
N	756		756		756		756	
Chi-square	50.25***		58.84***		55.18***		63.98***	
Log likelihood	-475.7769		-471.4799		-473.3094		-468.9108	

****p < 0 .01 **p < 0 .05 *p < 0.1*

[1] Top-end outliers winsorized at 99th percentile.

A5. Results of logit models with region fixed effects

The following table reflects coefficients of the models with region fixed effects, and number of conflict events between 2005 and 2021 (Section 6.4.3).

PSNP coverage (2021)	**(1)** $\widehat{\beta}$ $(\widehat{SE})$	**(2)** $\widehat{\beta}$ $(\widehat{SE})$
Poverty headcount rate (%)	0.0387***	0.0360***
	(0.0073)	*(0.0072)*
Population density	-0.0007***	-0.0006***
	(0.0002)	*(0.0002)*
No. dry months	0.0333***	
(SPEI 12-month timescale)	*(0.0106)*	
No. dry months		-0.0119*
(SPEI 36-month timescale)		*(0.0069)*
Population exposed to flood risk (%)	-0.0057	0.0023
	(0.0156)	*(0.0158)*
No. conflict events within and close to *woreda* (2005-21)	0.0113***	0.0113***
	(0.0029)	*(0.0036)*
Constant	-0.8029	-0.1548
	(0.4812)	*(0.4832)*
Region FE[2]	YES	YES
N	699	699
Chi-square	146.80***	134.80***
Log likelihood	-389.4762	-392.9770

****p < 0.01 **p < 0.05 *p < 0.1*

[1] Top-end outliers winsorised at 99th percentile.

[2] *Woreda*s in Afar, Benishangul Gumuz, Gambela, Harari, Addis Ababa and Dire Dawa regions are omitted.

A6. Results of logit models with conflict variable outliers winsorised at the 95th percentile

The following table reflects coefficients of the models with conflict variable outliers winsorised at the 95th percentile (Section 6.4.3).

PSNP coverage (2021)	(1) $\hat{\beta}$ $(\widehat{SE})$	(2) $\hat{\beta}$ $(\widehat{SE})$	(3) $\hat{\beta}$ $(\widehat{SE})$	(4) $\hat{\beta}$ $(\widehat{SE})$
Poverty headcount rate (%)	0.0337*** *(0.0063)*	0.0364*** *(0.0065)*	0.0313*** *(0.0063)*	0.0339*** *(0.0064)*
Population density	-0.0004** *(0.0001)*	-0.0004** *(0.0002)*	-0.0004** *(0.0002)*	-0.0004*** *(0.0002)*
No. dry months (SPEI 12-month timescale)	0.0304*** *(0.0088)*	0.0280*** *(0.0088)*		
No. dry months (SPEI 36-month timescale)			-0.0126** *(0.0061)*	-0.0130** *(0.0062)*
Population exposed to flood risk (%)	-0.0050 *(0.0102)*	-0.0051 *(0.0103)*	-0.0030 *(0.0102)*	-0.0031 *(0.0103)*
No. conflict events within and close to *woreda* (2005-19)[1]	-0.0006 *(0.0044)*		0.0010 *(0.0043)*	
No. conflict events within and close to *woreda* (2005-21)[1]		0.0107*** *(0.0031)*		0.0116*** *(0.0031)*
Constant	-1.7305*** *(0.2907)*	-2.0036*** *(0.2987)*	-1.0078*** *(0.2497)*	-1.3161*** *(0.2595)*
N	756	756	756	756
Chi-square	60.04***	71.90***	52.16***	66.21***
Log likelihood	-470.8811	-464.9537	-474.8208	-467.7956

****p < 0 .01 **p < 0 .05 *p < 0.1*

1 Top-end outliers winsorised at 95th percentile.

A7. Results of logit models with alternative conflict variables

The following table reflects coefficients of the models using two different conflict variables: i) the number of conflict events within a *woreda* boundary; and ii) the number of conflict events within a 0.1-degree buffer of its boundaries (Section 6.4.3). The outliers of these variables have not been winsorised.

PSNP coverage (2021)	(1) $\widehat{\beta}$ $(\widehat{SE})$	(2) $\widehat{\beta}$ $(\widehat{SE})$	(3) $\widehat{\beta}$ $(\widehat{SE})$	(4) $\widehat{\beta}$ $(\widehat{SE})$	(5) $\widehat{\beta}$ $(\widehat{SE})$	(6) $\widehat{\beta}$ $(\widehat{SE})$	(7) $\widehat{\beta}$ $(\widehat{SE})$	(8) $\widehat{\beta}$ $(\widehat{SE})$
Poverty headcount rate (%)	0.0334***	0.0341***	0.0310***	0.0315***	0.0353***	0.0347***	0.0329***	0.0322***
	(0.0064)	*(0.0063)*	*(0.0063)*	*(0.0063)*	*(0.0064)*	*(0.0063)*	*(0.0063)*	*(0.0063)*
Population density	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0005***	-0.0004**	-0.0005***
	(0.0001)	*(0.0002)*	*(0.0002)*	*(0.0002)*	*(0.0001)*	*(0.0002)*	*(0.0002)*	*(0.0002)*
No. dry months	0.0306***	0.0301***			0.0292***	0.0295***		
(SPEI 12-month timescale)	*(0.0088)*	*(0.0088)*			*(0.0088)*	*(0.0088)*		
No. dry months			-0.0125**	-0.0126**			-0.0131**	-0.0125**
(SPEI 36-month timescale)			*(0.0061)*	*(0.0061)*			*(0.0061)*	*(0.0061)*
Population exposed to flood risk (%)	-0.0049	-0.0051	-0.0029	-0.0031	-0.0054	-0.0052	-0.0033	-0.0031
	(0.0102)	*(0.0102)*	*(0.0102)*	*(0.0102)*	*(0.0103)*	*(0.0103)*	*(0.0102)*	*(0.0102)*
No. conflict events within 0.1º of	-0.0012		-0.0004					
***woreda* boundary** (2005-19)	*(0.0024)*		*(0.0024)*					
No. conflict events within *woreda*		0.0036		0.0046				
boundary (2005-19)		*(0.0053)*		*(0.0054)*				
No. conflict events within and close					0.0033*		0.0039**	
to *woreda* (2005-21)					*(0.0018)*		*(0.0018)*	
No. conflict events within *woreda*						0.0098**		0.0106**
boundary (2005-21)						*(0.0042)*		*(0.0042)*
Constant	-1.7163***	-1.7565***	-0.9844***	-1.0178***	-1.8356***	-1.8019***	-1.1262***	-1.0827***
	(0.2871)	*(0.2842)*	*(0.2460)*	*(0.2417)*	*(0.2893)*	*(0.2841)*	*(0.2490)*	*(0.2415)*
N	756	756	756	756	756	756	756	756
Chi-square	60.26***	60.46***	52.13***	52.80***	63.16***	65.32***	56.63***	58.12***
Log likelihood	-470.7701	-470.6696	-474.8376	-474.4992	-469.3202	-468.2393	-472.5883	-471.8412

****p < 0 .01 **p < 0 .05 *p < 0.1*

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