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Targeting Hunger or Votes?

The Political Economy of Humanitarian Transfers in Malawi

Jan Duchoslav, Edwin Kenamu, and Jack Thunde

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Abstract

Do electoral considerations play a role in the targeting of humanitarian transfers? We analyze the targeting of direct cash and food transfers distributed in Malawi in response to an exceptionally poor harvest following a late and erratic rainy season of 2015-16. Combining household survey data on transfers with a remotely sensed measure of drought and with the results of the 2014 and 2019 parliamentary elections, we show that transfers were disproportionately targeted at marginal constituencies. Rather than distributing the transfers based solely on need or mobilizing its tribal base, the government attempted to persuade swing voters to support its candidates in the next elections. We find no evidence that this strategy was successful at increasing the vote of ruling party candidates in subsequent elections.

Keywords: Political economy, Direct transfers, Disaster relief, Malawi, Voting
JEL codes: D72, H84, I38

1 Introduction

The notion that incumbent governments use discretionary spending to boost their re-election prospects is widely accepted and well documented, and concepts like "pork barrel politics" and the "political business cycle" are no longer exclusive to political and economic jargon, but have entered mainstream vocabulary. Targeting of government spending either at core voters in an attempt to mobilize their turn out at elections, or at marginal voters to gain their support, has been well documented for aggregate expenditures (Wright, 1974), infrastructure grants (Herron and Theodos, 2004) and even social protection programs (Brollo et al., 2020; Camacho and Conover, 2011). In this paper, we show that even the targeting of humanitarian programs is not immune to political influence.

We analyze the targeting of direct cash and food transfers distributed in Malawi in response to an exceptionally poor harvest following a late and erratic rainy season in 2015-16. We combine data from a nationally representative household survey conducted in the year following the poor harvest with a remotely sensed measure of drought and results from the 2014 and 2019 parliamentary elections which used a single-constituency first-past-the-post system. We find that the transfer program was disproportionately targeted at marginal constituencies in what seemed to be an attempt to swing them in favor of the ruling party, but find no evidence that the strategy was successful in increasing the vote share of ruling party candidates in the following elections.

We first provide an overview of existing literature on the political economy of direct transfers in Section 2, and describe the context of the study in Section 3. Section 4 then outlines our empirical

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strategy and is followed by a description of the three datasets in Section 5. We present our results in Section 6 and conclude in Section 7.

2 Direct transfers and elections

There is growing consensus that direct transfers—in cash or in kind—have economically significant effects on household and individual welfare. A large literature has documented the positive effects of such programs on food security (Bhalla et al., 2018), food consumption (Asfaw and Davis, 2018), productive asset accumulation (Handa et al., 2018), nutrition (Ahmed et al., 2019), education (Ralston et al., 2017), health and health–seeking behavior (Kusuma et al., 2016; Robertson et al., 2013), as well as psychosocial wellbeing (Natali et al., 2018) and aspirations (Kosec and Mo, 2017).

Insofar as the transfers are perceived to come from elected authorities, they tend to increase trust in and satisfaction with these authorities (Evans et al., 2019). However, empirical evidence on how this translates into political support is mixed (Kosec and Mo, 2019).

A number of studies show that transfers increase voter turnout (De La O, 2013; Galiani et al., 2019) as well as incumbents' vote share in elections (Bechtel and Hainmueller, 2011; Cerda and Vergara, 2008; De La O, 2013; Dionne and Horowitz, 2016; Galiani et al., 2019). For example, De La O (2013) found that early enrollment into a conditional cash transfer program significantly increased voter turnout and the incumbent's vote share in Mexico's 2000 presidential elections. Both size and timing of transfers matter: in a randomized experiment in Honduras, large transfers effected just before an election increased voter turnout and the incumbent's vote share more than cumulatively larger transfers that were spread out over time, suggesting that voters pay more attention to recent economic phenomena than to cumulative experience (Galiani et al., 2019). Cerda and Vergara (2008) found that increasing the proportion of people who receive government subsidies increased the votes for incumbent candidates in the 1989, 1993 and 1999 elections in Chile.[1] Dionne and Horowitz (2016) report similar electoral effects for the farm input subsidy program in Malawi, the beneficiaries of which were more likely to vote for the ruling party than non-beneficiaries.[2] Similarly, Bechtel and Hainmueller (2011) report that a large-scale government response to the 2002 Elbe floods a month before elections reversed an expected defeat for the ruling coalition in Germany, with the positive effects persisting for 7 years. Cole et al. (2012) come to a similar conclusion using rainfall, public relief, and election data from India, but find that the boost to electoral support following a successful disaster response is not sufficient to outweigh the punishment incumbents suffer at the ballot box for weather events beyond their control.

In contrast, Imai and Rivera (2019) studied the same Mexican program as De La O (2013) and found that it had no effect on electoral outcomes. Conditional cash transfers had no effect on voter turnout in the 2009 elections in Indonesia (Tobias et al., 2014) or on long-term voter alignment in Brazil (Zucco, 2013). In some cases, transfers may even hurt the incumbent as in Uganda, where youths empowered by a government business grant were less likely to vote for the ruling party and more likely to campaign for the opposition (Blattman et al., 2018).

A well-established body of literature documents the practice of discretionary spending by incumbents intended to improve their results in future elections. Government spending tends to increase (Nordhaus, 1975; Shi and Svensson, 2006) and its composition change (Brender and Drazen, 2013) in the run-up to elections. There is however less consensus regarding the targeting of such spending. Competing theoretical models predict that incumbents will target spending at their core supporters to mobilize

[1] Conversely, voters in municipal elections in Brazil punished candidates aligned with the president where compliance with transfer conditions was enforced (Brollo et al., 2020).

[2] The positive effect of transfers on incumbent's vote share may be due to a simultaneous increase in the turnout of incumbent's supporters and a decrease in the tournout of opposition supporters (Chen, 2013).

their base (Cox and McCubbins, 1986) or at easily persuadable swing voters in an attempt to convert them (Lindbeck and Weibull, 1987). Building on this work, Dixit and Londregan (1996) predict that core voters will be targeted if they can be reliably identified.[3] In the absence of reliable information about voters, spending will target swing constituencies.

Empirical evidence exists in support of both the mobilization model (Ansolabehere and Snyder, 2006; Nichter, 2008) and the persuasion model (Herron and Theodos, 2004). Kang (2015) offers a way to reconcile the two models, showing that subsidies from central government to local municipalities in South Korea are disproportionately targeted into districts with competitive races in the run-up to elections, but that governing party strongholds receive more such subsidies in total throughout the full duration of the election cycle.

The issue is further complicated in multiethnic states where voters often favor candidates and parties associated with their own ethnic group (Adida, 2015; Posner, 2004), expecting that coethnic politicians will provide better or more future economic and political goods to them (Carlson, 2015; Ferree and Horowitz, 2010; Wantchekon, 2003).[4] Considerations of ethnicity may be especially pertinent in countries like Malawi, where ethnic groups tend to be geographically segregated, which makes it easier for politicians to target spending along ethnic lines (Ejdemyr et al., 2018), and where entire political parties have strong ethnic associations (Dulani and Dionne, 2014; Posner, 2004). However, the extent to which political parties cater to their ethnic bases is are extremely context-dependent (Kramon and Posner, 2013).[5]

Whether incumbents use discretionary spending to mobilize their base or to persuade swing voters, it can be expected that they will use for such purposes any spending mechanism over which they exercise sufficient control—including direct transfers. Indeed, Brollo et al. (2020) document weaker enforcement of compliance with cash transfer conditions in Brazilian municipalities where mayors affiliated with the presidential coalition can run for reelection, and Camacho and Conover (2011) show that politicians in Colombian municipalities with more competitive elections manipulated eligibility scores for transfers more than politicians in municipalities with less competitive elections. Both studies consider well-established long-running social protection schemes. Focusing on the targeting of government response to an unprecedented crop failure in Malawi in relation to the results of preceding and subsequent parliamentary elections, we extend the literature on vote buying through government programs to a humanitarian context.

3 Context

Malawi is a landlocked country with a highly seasonal sub-tropical climate.[6] 95 percent of annual precipitation takes place during the warm-wet season between November and April, making this period the main agricultural season. Malawi's population of 17.6 million is predominantly rural (84 percent) and largely reliant for its livelihood on rain-fed agriculture during the main growing season.

[3] The incentive to target core voters becomes even stronger if their voting behavior can be monitored by the incumbent (Stokes, 2005).

[4] This instrumentalist explanation is by far the most common in recent literature on ethnic politics in Africa. The alternative explanation which builds on social identity theory, proposing that voters derive utility from an increased self-esteem brought about by belonging to the same ethnicity as those in power (Tajfel, 1982), would have little bearing on the targeting of government spending.

[5] See Golden and Min (2013) for an older but excellent overview of theoretical and empirical literature on the core an swing voter debate, ethnic favoritism, and other issues related to distributive politics.

[6] Thanks to its elevation, most of the country experiences relatively mild temperatures for its latitude with hot wet summers and dry winters (Köppen classification *Cwa*). Some lower-lying areas experience more tropical savanna climate with dry winters (Köppen classification *Aw*).

3.1 Malawi's administrative and electoral system

Malawi is divided into 28 administrative districts within 3 regions. Each district is headed by a District Commissioner who is in theory accountable to a partially elected district council but appointed (and recalled) by the central government.[7]

Each district contains several parliamentary constituencies (4.4 on average) and several Traditional Authorities (4.9 on average). The constituencies each elect a member of parliament using a single-vote first-past-the-post system. Traditional Authorities (TAs) are headed by hereditary chiefs.[8] They form one of the higher echelons of a customary governance structure of indirect rule which coexists with the direct-rule democratic structures.[9] Geographically, TA boundaries cross constituency boundaries and vice versa (so that parts of one TA may fall within different constituencies, and parts of one constituency may fall within different TAs). TA and constituency boundaries do not cross district boundaries (i.e. all TAs and constituencies belong to only one district).

District Councilors, Members of Parliament, and the President of the Republic are elected for 5-year terms in the Malawi tripartite elections, the last two of which took place on 20 May 2014 and 21 May 2019. In 2014, Peter Mutharika of the Democratic Progressive Party (DPP) won the presidential elections ahead of Lazarus Chakwera of the Malawi Congress Party (MCP), the incumbent Joyce Banda of the People's Party (PP), and Atupele Muluzi of the United Democratic Front (UDF). DPP candidates also won the plurality in both the parliamentary and district council elections. Voting took place largely along ethno-geographic lines: the Lomwe-dominated south of the country was carried by the DPP, the Yao-dominated southeast by the UDF, the Chewa-dominated center by the MCP and the Tumbuka-dominated north by the PP. Despite some exceptions, which are inevitable in a large number of races, the results of the parliamentary and local elections largely followed the same party-geographic patterns as the presidential election (Dulani and Dionne, 2014). A similar picture emerged from the 2019 elections, won again by Peter Mutharika ahead of Lazarus Chakwera, Saulos Chilima of the United Transformation Movement (UTM) and Atupele Muluzi in the presidential race, with DPP winning the plurality in the parliamentary and district council elections (Dulani and Dionne, 2014).[10,11] We refer to the Democratic Progressive Party (DPP) as the ruling party in the rest of the paper.

The presidential part of the tripartite elections is won by the candidate who receives the most votes nation-wide. Its results are only reported aggregated to the district level, so they do not lend themselves to identifying core and swing voters at a meaningful geographic scale. On the other hand, detailed results of the 2019 local elections have not been publicly released at the time of writing. We therefore use constituency-level parliamentary election results from 2014 and 2019 in our analysis.

[7] District councils consist of elected councilors (one for each ward within the district), elected members of parliament representing constituencies within the district, and unelected chiefs at the Traditional Authority rank.

[8] Both the geographical area and the chief in charge of it are referred to as Traditional Authorities.

[9] The highly hierarchical chiefly governance system is intertwined with the democratic one. Hereditary Village Headmen—whose approval is needed by their subjects to access many government services such as business registration, registration of land transactions or issuance of formal identification documents—are subordinate to a Group Village Headman (GVH), whom they elect from among themselves. GVHs are in turn subordinate to a hereditary TA. TAs report both to their centrally appointed District Commissioner and to one of Malawi's 7 Paramount Chiefs, 3 of whom are hereditary and 4 appointed by the president. At the same time, TAs are non-voting members of District Councils, who formally oversee the work of District Commissioners. See Eggen (2011) for a history of the co-evolution of the two governance systems and CLGF (2018) for an overview of the present local governance structure.

[10] The UTM largely replaced the PP as a dominant political force in the north of the country, while the DPP won in the UDF strongholds in the south-east.

[11] The results of the presidential part of the 2019 tripartite elections were annulled by the Constitutional Court in February 2020 due to widespread irregularities, and a re-run took place on 23 June 2020. In the re-run, Peter Mutharika (heading a DPP/UDF coalition) was defeated by Lazarus Chakwera (heading an MCP/UTM/PP coalition). The court however upheld the results of the parliamentary and district council results of the 2019 elections. See Table A1 in the Appendix for detailed electoral results.

3.2 The Food Insecurity Response Plan

Soon after the 2014 elections, Malawi was hit by a series of extreme weather events. The 2014/15 agricultural season started late and was very erratic, with extended periods of dryness interrupted by severe floods. As a result, 2.8 million Malawians required humanitarian assistance during the following lean season. Then, halfway between the 2014 and 2019 elections, the country experienced an unprecedented El Niño climate event from mid-2015 to mid-2016 that resulted in a severe drought in the southern and central parts of the country. In reaction to the ensuing harvest failure, the Government of Malawi in coordination with international donors launched the 2016/17 Food Insecurity Response Plan (FIRP) in June 2016. Consisting of activities in seven clusters—food security; health; education; nutrition; water, sanitation and hygiene (WASH); protection; and agriculture—FIRP not only aimed to prevent food insecurity in the affected population, but also among others to ensure their nutritional wellbeing and protection (Babu et al., 2018).

The food security cluster was by far the largest FIRP component in terms of both funding (USD 237.6 million) and targeted population (6.7 million beneficiaries). The assistance delivered under the food security cluster took the form of monthly direct cash and food transfers.[12] Distributions began in late July 2016 in Nsanje (the most affected district), covered all 24 affected districts by February 2017, and lasted until March 2017 (Babu et al., 2018). In the end, almost 40 percent of the Malawian population received a direct transfer during the 2016/17 lean season. About a fifth of the transfers were given out in cash modality and the rest in kind. Transfer value was the same regardless of modality or household size: each beneficiary household received either 50kg of maize, 10kg of beans and 5l of cooking oil per month or its monetary equivalent at prevailing market prices, i.e. approximately USD 20 at February 2017 exchange rates.

The food security cluster was led by the Department of Disaster Management Affairs (DoDMA)—a government agency within the Office of the Vice President—in coordination with the United Nations World Food Programme (WFP). The timing and number of transfers was set by DoDMA at the Traditional Authority (TA) level based on an assessment conducted by the Malawi Vulnerability Assessment Committee (MVAC) in May 2016 (and updated in September 2016). MVAC is a permanent multi-stakeholder body whose members include representatives of government agencies, donor organizations, non-governmental organizations, regional bodies and research institutions. It conducts annual assessments of threats to household livelihoods due to drought and other shocks (Babu et al., 2018).[13]

The centrally set TA-level beneficiary quotas were further subdivided by district officials to smaller administrative units all the way down to the village level. At the village level, beneficiary households were identified through a community-based targeting (CBT) process conducted by district officials. The CBT process centered on community-wide meetings during which participants first identified all households that satisfied a set of predefined criteria—known as the Joint Emergency Food Assistance Programme (JEFAP) criteria—and then selected the most vulnerable ones up to the assigned quota.[14] These households then received the FIRP transfers, distributed by WFP and international NGOs sub-contracted by

[12] The modality of transfer was set centrally at the level of Traditional Authority—a sub-division of the district. The decision was formally made by the government, but in practice, it was determined by international donors, most of whom preferred one modality over the other, and who each agreed to fund the transfers in specific geographic areas.

[13] MVAC assessments are based on weather data from the Department of Climate Change and Meteorological Services, food supply and demand information from the second round of the Agriculture Production Estimates Survey conducted by the Ministry of Agriculture, Irrigation and Water Development (MoAIWD) in February and March each year, the national food balance sheet also computed by the MoAIWD, local population estimates by the National Statistical Office, and primary data from field visits conducted by MVAC personnel. The assessments used the Household Economy Approach until 2016. Since 2017, MVAC has instead used the Integrated Phase Classification.

[14] The CBT process is far from perfect: not all households that satisfied the JEFAP criteria received transfers, and – more worryingly – some households that did not satisfy the criteria received transfers anyway (Duchoslav and Kenamu, 2018). There is also ample anecdotal evidence that local elites, especially chiefs, often interfere with the process. Despite these issues, the JEFAP criteria are a good predictor of transfer receipt at the household level.

WFP (Babu et al., 2018).

The complex set-up of the FIRP rendered it vulnerable to political influence at several entry points. At the highest level, the vulnerability projections produced by MVAC could be only as good as the statistics on which they were based. Many of them, including crucial information on food supply and demand, were produced by the Ministry of Agriculture, Irrigation and Water Development (which was headed by a minister from the ruling party) and required political clearance before use. The vulnerability projections were turned into TA-level distribution quotas by DoDMA, headed by the Vice President. The process through which the quotas were arrived at was obscure. Some district officials, whose job it was to determine village-level distribution quotas, complained about the TA-level quotas being too low, while others were perplexed by unreasonably high quotas, and many suggested that the process was subject to political capture (Babu et al., 2018). Complicating matters further is the fact that district officials are overseen by District Commissioners, who are accountable – among others – to their local members of parliament, and many of whom were appointed by the president. Given that power in Malawian political parties is highly centralized (Dulani, 2019), it is conceivable that any of these entry points (food availability statistics produced by the Ministry of Agriculture, vulnerability projections produced by MVAC, high-level distribution quotas produced by DoDMA, and local distribution quotas produced by district officials) may have been exploited to support ruling party candidates, even if the candidates themselves were not in a position to influence FIRP targeting directly.

As much as the high number of potential entry points for political meddling make the capture of FIRP feasible, it also makes it difficult to pinpoint the one that is being used. Malawi's small size does not help in this regard. While we can gauge if transfers are disproportionately targeted at marginal or stronghold constituencies, we cannot replicate the same analysis at a higher administrative level such as districts, of which there are too few in the country to serve as a meaningful unit of statistical analysis. The following section therefore outlines our strategy to empirically test whether political considerations play a role in FIRP targeting, but not through which channels they might do so.

4 Empirical strategy

FIRP was a response to drought and the ensuing harvest failure and food insecurity. The number of households in need of assistance in a given area thus depends on the severity of these stresses. Individual households were then targeted in a process based on a number of objective criteria and subjective community opinions (see Section 3.2 for details). The probability that any given household receives a FIRP transfer should therefore be a function of the severity of drought faced by the household and the targeting criteria:

$$Pr(T_i = 1|N_i, \boldsymbol{C_i}) = \Phi(\alpha + D_i\beta + \boldsymbol{C_i'}\boldsymbol{\gamma} + \varepsilon_i) \tag{1}$$

where T_i is a dummy indicating that household i received a direct transfer following the 2015/16 agricultural season, D_i is a measure of the severity of the drought faced by household i during the 2015/16 agricultural season, $\boldsymbol{C_i}$ is a vector of dummies indicating which targeting criteria were satisfied by household i, and ε_i is a stochastic error term.

If, however, the government exercises its control over the program to skew its resources towards constituencies where it hopes to affect electoral results in future elections, the results of the previous election will enter the probability function in one of two ways:

$$Pr(T_{ic} = 1|N_{ic}, \boldsymbol{C_{ic}}, S_c) = \Phi(\alpha + D_{ic}\beta + \boldsymbol{C_{ic}'}\boldsymbol{\gamma} + S_c^{14}\delta_1 + \varepsilon_{ic}) \tag{2}$$

or

$$Pr(T_{ic} = 1|N_{ic}, \boldsymbol{C_{ic}}, M_c) = \Phi(\alpha + D_{ic}\beta + \boldsymbol{C'_{ic}}\boldsymbol{\gamma} + |M_c^{14}|\delta_2 + \varepsilon_{ic}) \tag{3}$$

where S_c^{14} is the share of votes received by the ruling party candidate in constituency c in the 2014 parliamentary elections, M_c^{14} is the margin with which the ruling party candidate won over the nearest competitor (or lost to the victor) in constituency c in the 2014 parliamentary elections, the subscript $_{ic}$ refers to household i in constituency c and all other notation is the same as in (1).

By estimating (2) and (3), we can test if and how the government uses its control over the targeting of humanitarian transfers to improve its electoral prospects:

Hypothesis 1: Humanitarian transfers are disproportionately targeted at ruling party strongholds: $\delta_1 > 0$ in (2).

Hypothesis 2: Humanitarian transfers are disproportionately targeted at marginal constituencies: $\delta_2 < 0$ in (3).

If the government does use its control over the targeting of transfers to improve its electoral results, we can also test whether this strategy works by also considering the results of the 2019 parliamentary elections. By estimating:

$$S_c^{19} = \alpha + \bar{D}_c\beta + S_c^{14}\delta_3 + \bar{T}_c\zeta + \varepsilon_c \tag{4}$$

where S_c^{19} and S_c^{14} are the shares of votes received by the ruling party candidate in constituency c in the 2014 and 2019 parliamentary elections respectively, $\bar{D}_c$ is the average severity of drought faced by respondents in constituency c during the 2015/16 agricultural season and $\bar{T}_c$ is the proportion of respondents in constituency c who received a direct transfer following the 2015/16 agriculural season, we can test a third hypothesis:

Hypothesis 3: Voters reward transfers by voting for the ruling party candidate: $\zeta > 0$ in (4).

5 Data

We make use of three separate sources of data to test the hypotheses outlined in Section 4: a nationally representative household survey containing information on direct transfers, on the JEFAP criteria used in targeting FIRP transfers, as well as on drought exposure and agricultural yields; a high spatial resolution Standardized Precipitation Evapotranspiration Index (SPEI) drought dataset, which we use as our primary measure of drought severity; and constituency-level results of the 2014 and 2019 parliamentary elections.

5.1 Direct transfers and household characteristics

The Fourth Integrated Household Survey (IHS4) was conducted by Government of Malawi through its National Statistical Office (NSO) as part of the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative. The IHS4 was conducted between April 2016 and April 2017, i.e. immediately following the 2015/16 main agricultural season and during the 2016/17 FIRP response. The IHS is representative at the district level and at the urban and rural levels. It collected data on a wide range of topics including standard demographics, agricultural production, shocks faced by households, and information on participation in social safety nets and humanitarian programs from 12,447 households, 10,175 of which lived in rural areas. Of the rural households, 5,419 were interviewed after the first FIRP transfers were effected in their district.

IHS4 did not ask specifically about transfers from FIRP. Instead, it recorded whether respondent households received free maize and/or other food (as part of a social safety net or humanitarian programming rather than from individuals), and whether they received direct cash transfers from the government and/or other institutions. Given its immense scope, most direct transfers are likely to have been part of FIRP. We therefore treat all such transfers as part of FIRP.[15]

IHS4 allows us to identify households which satisfy the individual JEFAP criteria used to guide the CBT process. Specifically, we can identify households within the IHS4 dataset which:

1. are headed by children;
2. are headed by elderly people (more than 60 years old);
3. are headed by females;
4. are caring for orphaned children less than 18 years old;
5. have chronically ill members;
6. have children receiving supplementary or therapeutic feeding;
7. have experienced crop failure in the previous agricultural season.[16]

Household-level summary statistics for dummy variables indicating whether a household received a direct cash or food transfer following the 2015/16 agricultural season, whether the household was interviewed after transfer distribution had begun in its TA, and whether it satisfied each of the seven JEFAP criteria, are presented in Table 1.[17] Constituency-level summary statistics for the proportions of surveyed households who reported receiving transfers, who were interviewed after transfer distribution had begun in their TA, and who satisfied each of the JEFAP criteria, are presented in Table 2. The proportion of households who reported receiving a transfer is also illustrated in Figure 1, panel (a), where darker shades of green represent higher proportions of households receiving transfers.

IHS4 did not directly gather information about respondents' ethnicity, but it did record the main language spoken in their homes. Language is a poor proxy for ethnicity at the individual or household level in Malawi, because the Chewa language—Malawi's lingua franca—is spoken by many people who are not ethnically Chewa.[18] However, the proportion of households in a geographical area who speak a given language is a good proxy for the presence of the ethnicity associated with that language. In Table 2, we therefore also report the constituency-level proportions of households speaking the languages associated with the five largest ethnic groups in Malawi, which together make up 86.2 percent of the Malawian population: Chewa, Lomwe, Yao, Ngoni and Tumbuka.

[15] This probably introduces some noise to the data, but we have no reason to believe that the noise should not be random.

[16] The corresponding JEFAP criterion is two or more years of successive crop failure, but the IHS only records yield data for one previous agricultural season, so only one year of crop failure can be identified in the dataset. The criterion used in this report is therefore less strict than the original JEFAP one. We consider maize yields lower than 500kg/ha as indicative of crop failure. Households that satisfied at least two of the seven criteria were considered eligible to receive FIRP transfers.

[17] The proportion of the households who reported receiving a direct transfer following the 2015/16 agricultural season is much lower than the proportion of the Malawian population targeted by the transfer program. This is an artifact of the IHS4 survey, which interviewed some of the households before transfer distribution began in their TA. These households could not report receiving a transfer even though many of them would benefit from the program after they were interviewed. We account for this possibility in our empirical models.

[18] Chewa is the main language in 66.2 percent of households, even though the Chewa make up only 34.4 percent of Malawi's population. Conversely, only 2.1 percent of households speak Lomwe, even though the Lomwe—Malawi's second largest ethnic group—make up 18.9 percent of the population (NSO, 2019).

5.2 Drought

The Standardized Precipitation Evapotranspiration Index (SPEI) takes into account the difference between precipitation and potential evapotranspiration[19] to calculate climatic water balance at different time scales between 1 and 48 months, and is expressed in terms of standard deviations from a long-run mean (Vicente-Serrano et al., 2010). Thanks to its multiscalar nature, it is a better predictor of agricultural drought than earlier drought indices, especially on time scales between 3 and 6 months (Vicente-Serrano et al., 2012).

In this paper, we use a SPEI dataset constructed by Peng et al. (2019) for Africa. This dataset has a higher spatial resolution (0.05°) than the original SPEI dataset by Vicente-Serrano et al. (2010) (0.5°). It also relies less on weather station data, which are sparse in Africa, making instead extensive use of satellite data. Following Harari and La Ferrara (2018), we use the average monthly SPEI value (at the 4-month time scale) during the main growing season (November through April) as an exogenous measure of the severity of drought faced by the households in the IHS4 dataset. The resulting raster is depicted in Figure 1, panel (b), where darker shades of orange represent more sever drought.

Table 1: Summary statistics by household

Variable	Mean	Std. Dev.	Min.	Max.	N
Received transfer	0.232	0.422	0	1	10,175
Distribution	0.418	0.493	0	1	10,175
Child head	0.001	0.038	0	1	10,175
Elderly head	0.181	0.385	0	1	10,175
Female head	0.308	0.462	0	1	10,175
Caring for orphans	0.021	0.144	0	1	10,175
Chronically ill member	0.227	0.419	0	1	10,175
Children on supplementary/therapeutic feeding	0.022	0.147	0	1	10,175
Harvest failure	0.231	0.421	0	1	10,175
SPEI	−0.894	0.413	−1.664	0.969	9,328
Experienced drought	0.810	0.393	0	1	10,175
Maize yield (kg/ha)	863.667	810.724	2.073	3,013.48	5,465

Notes: Distribution = dummy equal to 1 if household was interviewed after transfer distribution began in their TA.

To verify robustness to the type of drought measure, we also consider self-reported data from IHS4. Specifically, we use maize yields (calculated from self-reported harvest and plot size data from IHS4) and a dummy variable indicating whether a household reported that it faced drought or irregular rains during the 12 months preceding the household interview. Household-level summary statistics for all three drought severity measures are presented in Table 1 while the corresponding constituency-level summary statistics are presented in Table 2.[20,21]

[19] Evapotranspiration is a set of processes through which water leaves soil, and includes bare-soil evaporation, open-water evaporation, sublimation (where applicable), transpiration by plants, and interception loss (precipitation which evaporates from surfaces such as the canopy before reaching the soil). Potential evapotranspiration is the amount of evapotranspiration that would occur if sufficient amount of water were available.

[20] The Peng et al. (2019) dataset masks out barren and sparsely vegetated areas, including large water bodies because of lower reliability of SPEI over areas with low hydroclimatic variability. Due to this and the pixelated nature of the dataset some lake shore areas lack SPEI values, which reduces the number of household observations and constituencies for which SPEI values are available to 9,328 and 168 respectively.

[21] Depending on the date of the interview, questions from which the yield variable was constructed were asked either about the 2014/15 agricultural season or the 2015/16 agricultural season. We only take consider responses pertaining to the 2015/16 agricultural season. As a result, average maize yield values are only available for 5,465 households and for 168 constituencies.

Figure 1: Spatial distribution of main variables of interest

(a) Received transfer (b) Drought severity (c) Ruling party vote share (d) Ruling party margin

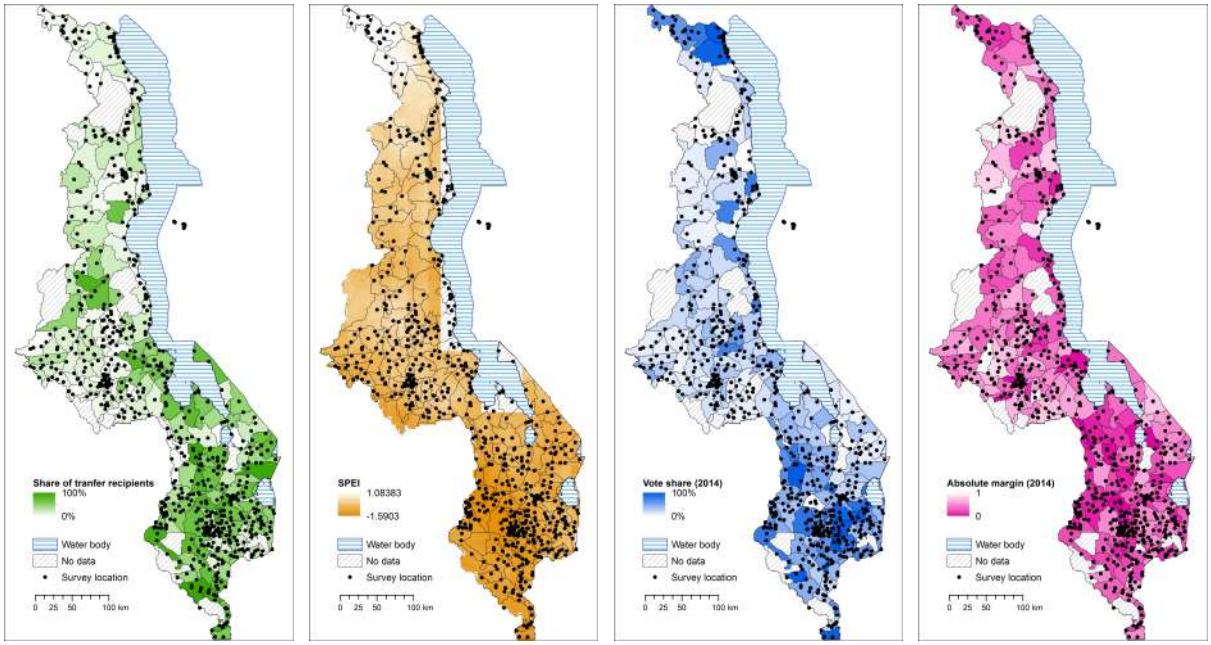


Table 2: Summary statistics by constituency

Variable	Mean	Std. Dev.	Min.	Max.	N
Received transfer	0.222	0.196	0	0.834	176
Child head	0.001	0.004	0	0.035	176
Elderly head	0.179	0.067	0	0.373	176
Female head	0.303	0.102	0.022	0.563	176
Caring for orphans	0.021	0.025	0	0.172	176
Chronically ill member	0.228	0.094	0	0.511	176
Children on supplementary/therapeutic feeding	0.022	0.037	0	0.161	176
Harvest failure	0.225	0.158	0	0.764	176
SPEI	−0.794	0.425	−1.543	0.907	168
Experienced drought	0.791	0.158	0.257	1	176
Maize yield (kg/ha)	885.968	391.289	49.239	2,534.458	168
Chewa	0.582	0.38	0	1	176
Lomwe	0.018	0.038	0	0.25	176
Yao	0.096	0.234	0	1	176
Ngoni	0.024	0.092	0	0.625	176
Tumbuka	0.126	0.301	0	1	176
Other language	0.154	0.267	0	1	176

Notes: At the constituency level, SPEI, self-reported drought exposure, and maize yield are the mean values reported by households in each constituency. The remaining variables are the proportions of households who possess the given characteristic in each constituency.

5.3 Election results

The 2014 and 2019 parliamentary elections (both part of larger tripartite elections during which the president and local governments were also elected) took place in 193 parliamentary constituencies to elect members of parliament using a first-past-the-post voting system.[22] Using official election results, we construct four measures of electoral outcomes for each constituency: the share of votes received by the ruling party candidate in 2014 and 2019, the margin of vote share which the ruling party candidate had over the runner-up (if the seat was won by the ruling party) or which the victor had over the ruling party candidate (if the seat was won by the opposition), and the Herfindahl–Hirschman Index (HHI) of party support as a measure of political competition.[23]Summary statistics for these variables are presented in Table 3 and depicted in Figure 1, panels (c) and (d), where darker shades of blue represent higher vote share for ruling party candidates, and darker shades of pink represent more competitive constituencies.

Table 3: Ruling party parliamentary candidates results

Variable	Mean	Std. Dev.	Min.	Max.	N
Vote share 2014	0.209	0.17	0	0.9	175
Won 2014	0.234	0.425	0	1	175
Winning margin 2014	0.209	0.178	0.001	0.856	41
Losing margin 2014	−0.303	0.169	−0.886	−0.004	134
Margin 2014	−0.183	0.276	−0.886	0.856	175
|Margin 2014|	0.281	0.175	0.001	0.886	175
HHI 2014	0.315	0.107	0.13	0.822	175
Vote share 2019	0.272	0.191	0	0.872	175

Notes: HHI = Herfindahl–Hirschman Index.

6 Results

We start by modeling the probability of receiving a transfer without regard to political circumstances. Since the survey interviews began in April 2016, i.e. almost 4 months before the first transfer distribution began, we have to account for the fact that some respondents who go on to receive FIRP transfers could not yet report on the fact. We account for this possibility by adding time controls to the model described by equation (1) above: a dummy indicating that the respondent was interviewed after FIRP transfer distribution began in their TA and month of interview fixed effects.[24] In combination with dummies representing the targeting criteria and time controls, the Standardized Precipitation-Evapotranspiration Index (SPEI) is a better predictor of whether or not a household received direct transfers than self-reported exposure to drought or self-reported maize yield (Table 4), correctly predicting which households benefited from direct transfers in 79 percent of cases and thus outperforming the alternative drought severity measures. The superior performance of SPEI over self-reported measures of drought severity in predicting direct transfers can be clearly seen by comparing the receiver operating characteristic (ROC) curves of the three models in Figure 2, where models with better predictive power are represented by curves further away from the diagonal.[25]

[22]3 constituencies are not represented in IHS4, 14 are entirely urban, and 8 do not overlap with the SPEI dataset.

[23]$HHI = \sum_{i=1}^{N} s_i^2$ where s_i is the vote share of part i and N is the number of parties competing in a constituency. The lower the HHI value, the more competitive the constituency.

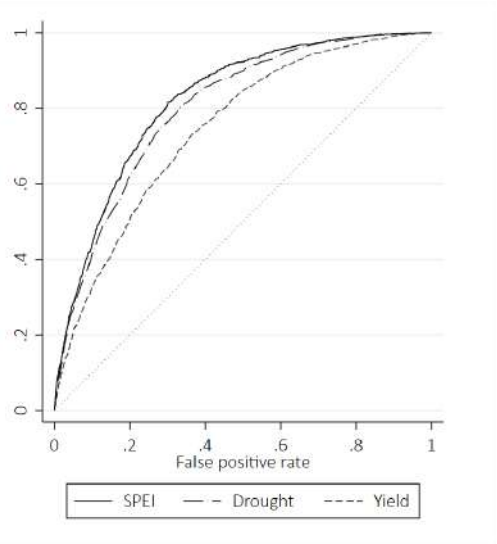
[24]There is no single best way to control for the distribution schedule in our context. Using month of interview fixed effects alone would ignore the fact that transfer distribution began at different times in different TAs. Using the distribution dummy alone would preclude us from detecting any mistargeting in terms of timing rather; it would only allow detection of mistargeting in terms of number of beneficiaries. To partially overcome these drawbacks, we include both distribution dummy and month of interview fixed effects in our models. Controlling for an interaction of month of interview and TA

Table 4: SPEI is a good predictor of direct transfers

	Received transfer		
	(1)	(2)	(3)
SPEI	-0.155***		
	(0.032)		
Experienced drought		0.084***	
		(0.018)	
Maize yield (t/ha)			-0.029*
			(0.015)
Targeting criteria	yes	yes	yes
Distribution	yes	yes	yes
Month FE	yes	yes	yes
N	9,294	10,175	5,459
Pseudo R^2	0.225	0.210	0.124
AUC[26]	0.821	0.801	0.744

Notes: Probit average marginal effects. Standard errors clustered by TA in parentheses. Distribution = dummy equal to 1 if household was interviewed after transfer distribution began in their TA. AUC = area under ROC curve. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: ROC curves



Having established that SPEI is a better predictor of direct transfer receipt than self-reported experience of drought or self-reported maize yield, we next investigate whether the targeting of humanitarian transfers is influenced by past electoral results. We do so by adding to the basic model (model (1) in Table 5, based on equation (1) in section 4) the vote share of the ruling party candidate in the 2014 parliamentary elections (model (2), based on equation (2) in section 4), the absolute value of the margin with which the ruling party candidate won or lost (model (3), based on equation (3) in section 4), or both (model (4)).[27]

The vote share of the ruling party candidate has no detectable effect on the probability that households in the constituency received humanitarian transfers following the 2015/16 agricultural season. However, the winning or losing margin of the ruling party candidate enters the equation in a manner consistent with the hypothesis that humanitarian transfers are disproportionately targeted towards marginal constituencies, presumably in an attempt to improve the ruling party's prospects in future elections: Households in constituencies where the ruling party candidate narrowly won or narrowly lost in 2014 received more humanitarian assistance than they would if transfer targeting was based solely on their exposure to drought. By a simple arithmetic calculation, the probability that a household in

fixed effect is a solution which would overcome the drawbacks entirely, but for which we lack degrees of freedom.

[25] An ROC curve illustrates the diagnostic ability (predictive power) of a model with a binary dependent variable, i.e. how often the model correctly predicts the dependent variable. Binary outcome models estimate the probability that the dependent variable takes on a positive value, and assign that value to all observations that exceed a selected probability threshold, usually 0.5. An ROC curve plots for all thresholds (from 0 to 1) the true positive rate (the proportion of actual positives that are correctly identified as such by the model) against the false positive rate (the proportion of actual negatives that are misidentified by the model as positives). At a threshold of 0, all observations will be identified as positive, so the true positive rate will be 1 (all true positives will be identified as such), but so will the false positive rate (all true negatives will be misidentified as positives). At the threshold of 1, all observations will be identified as negative, so the false positive rate will be 0 (all true negatives will be correctly identified as such), but the true positive rate will also be 0 (all true positives will be misidentified as negatives). A diagonal between these two extremes represents a model with no diagnostic ability whatsoever. The better the diagnostic ability of a model, the further its ROC is from the diagonal.

[26] The differences in AUC between models are small in magnitude. However, the difference in AUC between the basic model (1) and the models (3) and (4) which include winning/losing margins are significant at the 1 percent level, while the difference between the basic model (1) and the stronghold model (2) is statistically insignificant. The differences in AUC between the stronghold model and the models (3) and (4) which include winning/losing margins are significant at the 5 percent level. The difference in AUC between models (3) and (4) is only marginally significant at the 10 percent level.

[27] Note that the outcome variable is observed at the household level, as are most explanatory variables except for those on ruling party electoral results in 2014, which are observed at the constituency level. Standard errors must be clustered at the constituency level in models (2), (3), and (4), which include electoral results. Additionally, standard errors in all four models must be clustered at the TA level, where transfer allocation quotas are determined.

Table 5: Transfers are skewed towards marginal constituencies

	Received transfer			
	(1)	(2)	(3)	(4)
Vote share 2014		0.036		0.001
		(0.073)		(0.069)
|Margin| 2014			-0.188**	-0.187**
			(0.077)	(0.078)
SPEI	-0.155***	-0.147***	-0.123***	-0.123***
	(0.032)	(0.035)	(0.033)	(0.032)
Targeting criteria	yes	yes	yes	yes
Distribution	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
N	9,246	9,246	9,246	9246
Pseudo R^2	0.224	0.224	0.230	0.230
AUC	0.821	0.820	0.823	0.823

Notes: Probit average marginal effects. Standard errors clustered by TA in all four models and by constituency in models (2), (3) and (4) in parentheses. Distribution = dummy equal to 1 if household was interviewed after transfer distribution began in their TA. AUC = area under ROC curve. Compared to the same model in Table 4, model (1) here excludes 48 households from one constituency where parliamentary elections were postponed due to the death of one of the candidates during the official campaign period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a closely contested constituency (with a winning/losing margin approaching 0) received a transfer was 5.3 percentage points higher than the probability that a household from a constituency with an average margin (0.281) received a transfer. This is quite a sizable (dis)advantage considering that the overall probability of receiving a transfer was 22.2 percent for rural Malawian households. The additional transfers came at the expense of households in constituencies that were safely won by either the ruling party or the opposition received.

Result 1: Humanitarian transfers are disproportionately targeted at marginal constituencies.

The result is robust to using the Herfindahl–Hirschman Index instead of absolute margin as a measure of constituency competitiveness (see Table A2 in the Appendix). Using self-reported experience of drought and maize yield as alternative measures of drought severity also leads to similar, although less precise, results (Tables A3 and A4 in the Appendix).[28]

Controlling for the ethnic makeup of constituencies proxied by language does not change the results either (Table A5 in the Appendix), which may come as a surprise in a political context where the ruling party is generally regarded as drawing support from—and catering to—a different ethnic group than other major parties.[29] If the electorate is strictly divided along ethnic lines, electoral gains should only be possible by mobilizing a larger share of ones own ethnic base. Wy would the ruling party

[28] When using self-reported drought severity measures, the estimated coefficients on ruling party vote share are positive and statistically significant (models (2) in Tables A3 and A4), seemingly giving support to the hypothesis that transfers are disproportionately targeted at ruling party strongholds. However, both the magnitude and statistical significance of these coefficients are drastically reduced when winning/losing margin is also introduced in the model (models (4) in Tables A3 and A4). On the other hand, the coefficient and standard errors on winning/losing margin (models (3) in Tables A3 and A4) barely change when ruling party vote share is included. This suggests that significance and magnitude of the vote share coefficient in models (2) is therefore likely an artefact of the dataset: Ruling party vote share and the absolute value of ruling party losing margin are collinear, and ruling party candidates lost in the majority of constituencies (see Table A1 in the Appendix).

[29] Table A6 shows how ethnic composition of constituencies affects the support for the candidates of each major party. It shows that the ruling party (DPP) is dominated by—and attracts the support of—the Lomwe. The MPC is Chewa-dominated and attracts Chewa support. The UDF attracts primarily Yao supporters and the UTM is popular among the Ngoni. Although Joyce Banda is a Yao, her party (PP) does not have a well defined ethnic support base.

target transfers at swing constituencies in such a political reality? The answer may lie in the historical experience of the ruling party, which managed to break down the ethno-regional voting blocks when it registered a landslide victory in the 2009 elections on the back of a popular agricultural input subsidy program (Ferree and Horowitz, 2010; Dulani and Dionne, 2014). The ruling party may have been trying a similar strategy with humanitarian transfers.

Did voters respond by rewarding ruling party candidates for humanitarian transfers at the ballot box? We turn to constituency-level data to answer this question, exploring the relationship between the proportion of proportion households in a constituency who reported receiving a transfer (aggregated from household survey data to constituency level) and the electoral performance of the ruling party in the subsequent election. The estimation results reported in Table 6 do not provide any evidence to suggest that transfers distributed in 2016/17, i.e. in the middle of an electoral term, have any impact on the success of ruling party candidates in the 2019 elections. Using self-reported experience of drought and maize yield as alternative measures of drought severity leads to similar results (Table A7 in the Appendix). However, we should be careful not to interpret this null result as evidence that humanitarian transfers do not affect voting behavior at all. Previous work suggests that voters discount the past[30] in a way that their voting behavior is more strongly affected by transfers effected just before elections than those taking place in the middle of the electoral cycle. While we can say with a reasonable degree of certainty that transfers distributed more than two years before the 2019 parliamentary elections did not affect the results,[31] it is plausible that transfers distributed closer to elections did. We cannot, however, test this hypothesis with currently available data.

Table 6: Voters do not reward transfers with votes for ruling party candidates

	Vote share 2019	
	(1)	(2)
Received transfer	0.011	-0.005
	(0.078)	(0.072)
Vote share 2014	0.443***	0.363***
	(0.087)	(0.111)
SPEI	-0.071*	-0.121***
	(0.040)	(0.039)
Targeting criteria	yes	yes
Language	no	yes
N	166	166
Adj. R^2	0.237	0.322

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Result 2: Voters do not reward transfers distributed in the middle of the electoral term by voting for ruling party candidates.

[30] See Yi et al. (2006) for a general discussion of discounting of past outcomes.

[31] The household survey from which we aggregate the proportion of households in a constituency who received transfers was not designed to be representative at the constituency level, but only at the district level. There are more than four times as many constituencies as there are districts in Malawi, so the measure will be farily noisy. This has likely affected the size of the standard errors in our estimations and thus their power, but not the magnitude of the estimated coefficients, which is small enough to be practically meaningless.

7 Conclusion

One of the primary goals of political parties is to get as many of their candidates as possible elected into public office. Once in power, it is logical for parties to use all legal means at their disposal to help their candidates retain the public offices they hold. A well-established body of research shows that public funds are often used to this end, not always in line with their stated purpose. Building upon this literature, we investigate whether the targeting of ad hoc humanitarian spending also suffers from such political influence.

We analyze the targeting of direct cash and food transfers distributed in Malawi in response to an exceptionally poor harvest following late and erratic rains in 2015-16. We combine household survey data on the receipt of cash and food transfers in the aftermath of the failed harvest with the results of the 2014 and 2019 parliamentary elections. Controlling for the need and eligibility for assistance as measured by a remotely sensed drought index and a number of time-invariant household characteristics, we find that the transfer program was disproportionately targeted at households in marginal constituencies, and that the difference in the chances that a household received transfers was sizable between marginal and safe constituencies. In other words, we find evidence that humanitarian transfers were used to persuade swing voters to support the ruling party rather than to mobilize the ruling party's core voters. This is a noteworthy finding in a political environment where parties are generally regarded as aligned with—and catering to the needs of—specific ethnic groups. Within the context of the scholarly debate on the use of persuation or mobilization in distributive politics, our results therefore fall squarely in the persuasion camp.

We do not, however, find any evidence that voters responded to the persuation strategy by supporting ruling party candidates in the next election. Unfortunately, we are unable to tell whether this is because voters do not reciprocate favorable humanitarian treatment at all, or because they only reciprocate favors granted shortly before elections, as some previous research suggests. Data on similar transfers that took place closer to political elections would be needed to answer this question.

Another question which we must leave unanswered due to data limitations concerns the specific channels through which humanitarian transfers are politicized. Future research in this direction could not only improve the understanding of distributive politics, but also suggest control mechanism to limit the prevalence of political capture of essential humanitarian programs.

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Appendix A: Tables

Table A1: Election results 2014–2020

	2014	2019	2020
Panel A: Presidential vote share			
Peter Mutharika (DPP)	36.42%	38.57%	39.92%
Lazarus Chakwera (MCP)	27.84%	35.43%	59.34%
Joyce Banda (PP)	20.20%	—	—
Saulos Chilima (UTM)	—	20.24%	—
Atupele Muluzi (UDF)	13.72%	4.67%	—
Other candidates	1.81%	1.09%	0.74%
Panel B: Parliamentary seats won			
DPP	51	62	
MCP	48	55	
PP	26	5	
UTM	—	4	
UDF	14	10	
Other parties	2	1	
Independents	52	55	
Panel C: Local government seats won			
DPP	165	161	
MCP	131	160	
PP	65	4	
UTM	—	39	
UDF	57	20	
Other parties	4	2	
Independents	35	74	

Notes: DPP = Democratic Progressive Party, MCP = Malawi Congress Party, PP = People's Party, UTM = United Transformation Movement, UDF = United Democratic Front. — = candidate/party did not participate. Local government election results include races for district council seats in rural areas as well as city, town and municipal council seats in urban areas.

Table A2: Transfers are skewed towards more competitive constituencies

	(1)	(2)
Vote share 2014		0.092
		(0.072)
HHI 2014	-0.322**	-0.357***
	(0.132)	(0.137)
SPEI	-0.140***	-0.121***
	(0.034)	(0.033)
Distribution began	0.146***	0.145***
	(0.029)	(0.028)
Month FE	yes	yes
Targeting criteria	yes	yes
N	9,246	9,246
Pseudo R^2	0.230	0.231
AUC	0.822	0.823

Notes: Probit average marginal effects. Standard errors clustered by TA in all four models and by constituency in models (2), (3) and (4) in parentheses. HHI = Herfindahl–Hirschman Index. AUC = area under ROC curve. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Transfers are skewed towards marginal constituencies (alternative measure of drought severity = self-reported experience of drought)

	Received transfer			
	(1)	(2)	(3)	(4)
Vote share 2014		0.151**		0.084
		(0.070)		(0.069)
|Margin| 2014			-0.252***	-0.227***
			(0.075)	(0.076)
Experienced drought	0.085***	0.085***	0.083***	0.083***
	(0.018)	(0.018)	(0.017)	(0.017)
Targeting criteria	yes	yes	yes	yes
Distribution	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
N	10,127	10,127	10,127	10,127
Pseudo R^2	0.209	0.212	0.220	0.221
AUC	0.801	0.805	0.810	0.811

Notes: Probit average marginal effects. Standard errors clustered by TA in all four models and by constituency in models (2), (3) and (4) in parentheses. AUC = area under ROC curve. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Transfers are skewed towards marginal constituencies (alternative measure of drought severity = self-reported maize yield)

	Received transfer			
	(1)	(2)	(3)	(4)
Vote share 2014		0.259**		0.156
		(0.111)		(0.105)
|Margin| 2014			-0.419***	-0.376***
			(0.106)	(0.108)
Maize yield (t/ha)	-0.029*	-0.028*	-0.030*	-0.030*
	(0.015)	(0.016)	(0.016)	(0.016)
Targeting criteria	yes	yes	yes	yes
Distribution	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
N	5,422	5,422	5,422	5,422
Pseudo R^2	0.122	0.129	0.142	0.145
AUC	0.744	0.751	0.758	0.762

Notes: Probit average marginal effects. Standard errors clustered by TA in all four models and by constituency in models (2), (3) and (4) in parentheses. AUC = area under ROC curve. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Transfers are skewed towards marginal constituencies even when controling for their ethic makeup

	Received transfer			
	(1)	(2)	(3)	(4)
Vote share 2014		0.010		-0.019
		(0.074)		(0.078)
|Margin| 2014			-0.188**	-0.190**
			(0.078)	(0.079)
SPEI	-0.134***	-0.133***	-0.109***	-0.110***
	(0.029)	(0.030)	(0.030)	(0.030)
Targeting criteria	yes	yes	yes	yes
Distribution began	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
Language	yes	yes	yes	yes
N	9246	9246	9246	9246
Pseudo R^2	0.235	0.235	0.241	0.241
AUC	0.821	0.820	0.822	0.822

Notes: Probit average marginal effects. Standard errors clustered by TA in all four models and by constituency in models (2), (3) and (4) in parentheses. AUC = area under ROC curve. Compared to the same model in Table 4, model (1) here excludes 48 households from one constituency where parliamentary elections were postponed due to the death of one of the candidates during the official campaign period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Party results depend on ethnic composition of constituency

	(1) DPP	(2) MCP	(3) PP	(4) UDF	(5) UTM
Panel A: 2014					
Chewa speakers (%)	-0.161***	0.341***	-0.153***	-0.0206	0
	(-4.13)	(7.39)	(-4.57)	(-0.83)	(.)
Yao speakers (%)	-0.246***	-0.0250	-0.134**	0.390***	0
	(-4.55)	(-0.39)	(-2.89)	(11.38)	(.)
Tumbuka speakers (%)	-0.234***	0.118*	0.0389	-0.0713*	0
	(-4.88)	(2.07)	(0.95)	(-2.35)	(.)
Lomwe speakers (%)	1.948***	-2.059***	-0.894***	0.167	0
	(6.96)	(-6.20)	(-3.73)	(0.94)	(.)
Ngoni speakers (%)	0.180	-0.0769	-0.293**	0.00787	0
	(1.58)	(-0.57)	(-2.99)	(0.11)	(.)
N	176	176	176	176	176
adj. R^2	0.374	0.414	0.302	0.568	.
Panel B: 2019					
Chewa speakers (%)	-0.139**	0.155**	-0.0566*	-0.0122	-0.0558*
	(-2.78)	(2.93)	(-2.18)	(-0.60)	(-2.24)
Yao speakers (%)	-0.0783	-0.211**	0.0245	0.279***	-0.0724*
	(-1.13)	(-2.87)	(0.68)	(9.84)	(-2.09)
Tumbuka speakers (%)	-0.0577	-0.00511	0.00877	-0.0227	0.0195
	(-0.94)	(-0.08)	(0.27)	(-0.91)	(0.64)
Lomwe speakers (%)	2.073***	-2.430***	-0.200	-0.00643	-0.195
	(5.77)	(-6.37)	(-1.07)	(-0.04)	(-1.09)
Ngoni speakers (%)	-0.0812	-0.0739	-0.0237	-0.0213	0.303***
	(-0.55)	(-0.47)	(-0.31)	(-0.36)	(4.13)
N	176	176	176	176	176
adj. R^2	0.183	0.284	0.063	0.477	0.165

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Voters do not reward transfers with votes for ruling party candidates (alternative measures of drought severity)

	Vote share 2019					
	(1)	(2)	(3)	(4)	(5)	(6)
Received transfer	0.011	-0.005	0.059	0.071	0.063	0.078
	(0.087)	(0.082)	(0.081)	(0.079)	(0.082)	(0.080)
Vote share 2014	0.443***	0.363***	0.480***	0.422***	0.455***	0.419***
	(0.082)	(0.096)	(0.078)	(0.095)	(0.079)	(0.096)
SPEI	-0.071*	-0.121***				
	(0.038)	(0.040)				
Experienced drought			0.063	0.035		
			(0.091)	(0.098)		
Maize yield (t/ha)					-0.055	-0.054
					(0.048)	(0.048)
Targeting criteria	yes	yes	yes	yes	yes	yes
Language	no	yes	no	yes	no	yes
N	166	166	174	174	166	166
Adj. R^2	0.237	0.322	0.226	0.281	0.227	0.280

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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