For Everything There is a Season: Seasonality and Retrospective Voting in African Elections

Brian Engelsma*
University of California, San Diego

January 13, 2023

Abstract

Are African elections subject to seasonal effects? If so, why? I argue that agricultural seasonality patterns election outcomes by influencing voters' retrospective performance evaluations. When countries hold elections after harvests, as households receive lump income payments, voters reward incumbents with their support. To consider this argument, I use satellite imagery to construct a measure of agricultural seasons and pair this measure with both an original dataset of 145 executive-election results from 32 countries broken down by subnational unit, and 120,000 survey responses from three Afrobarometer rounds. Analyzing all African election results, I first show a curvilinear relationship between the time from harvest and support for the incumbent government. Initially, voters are more likely to support incumbents following a harvest, but this relationship eventually reverses before the next harvest. To account for endogenous election timing, I examine quasi-experimental evidence from two Zambian by-elections triggered by the untimely deaths of Presidents Levy Mwanawasa in 2008 and Michael Sata in 2015. Finally, to understand why these patterns exist, I probe for causal mechanisms by considering how survey responses vary by season. Respondents' approval of their government's performance on the economy, improving living conditions, and keeping prices down all vary by season. This paper improves our understanding of economic voting in Africa, providing clear evidence that regular changes in agricultural conditions are associated with a voter's support of incumbent politicians.

Word Count: 6839

*All errors are my own.

While the earth remaineth, seedtime and
harvest, and cold and heat, and summer
and winter, and day and night shall not cease.
- Genesis 8:22

Do African incumbents benefit if elections are held after harvests? Rain-fed agriculture remains a central aspect of economic and social life in sub-Saharan African states. However, we know little about how this reality shapes electoral and political outcomes across the continent. In this paper, I make two claims. First, when countries hold elections after a harvest, incumbent governments do better at the polls. However, as households exhaust their savings and living conditions worsen over the year, voters begin to sour and increasingly punish incumbent governments. Second, I argue this pattern is attributable to retrospective voting, changes in how individual voters evaluate the government's performance due to their present economic situation. I find support for this argument in analyses of election results and nationally-representative surveys from across the continent, using a measure of seasonality derived from satellite imagery. For African voters, changes in agricultural conditions are a voting issue.

According to the World Bank, the agricultural sector employs over half of all African workers.[1] In most African countries, less than five percent of agricultural land is irrigated. These two facts suggest that in many countries the modal household relies on rain-fed agriculture to meet its consumption needs. However, rainfall and other growing conditions are not constant throughout the year. Environmental realities limit when households can plant and harvest crops. Work in development economics and public health show seasonal patterns in household income, labor, disease environments, and many other outcomes. Do these seasonal effects extend to electoral outcomes?

I argue that election outcomes vary systematically according to agricultural seasons. After harvests, when households enjoy a sudden, yet predictable, earnings windfall, voters

[1] The actual number of Africans working in agriculture may be higher due to informal employment and family labor, as well as people farming plots of land as a secondary income source.

reward incumbent governments with their vote. As households increasingly draw from savings, loans, and local support networks to meet consumption needs, attitudes towards the government shift and voters punish incumbents at the polls. This trend continues until the coming harvest when households again receive a jolt in earnings and accordingly reward incumbents.

To consider my argument, I first create a measure of agricultural seasons using remote-sensed data from Landsat satellites. For every first-order subnational unit in sub-Saharan Africa, I calculate the commonly used Normalized Difference Vegetation Index (NDVI) at 8-day intervals. For every year, I find the average date of maximum-NDVI, a proxy for harvests. Next, I pair this measure with an original panel dataset of 145 executive-election results from 32 countries broken down by subnational unit, creating a measure of time from harvest. I then estimate a series of two-way fixed effects regressions, regressing the incumbent's share of the vote and margin of victory or defeat on my measure of time from harvest.

One challenge with this approach is non-random election timing. If incumbents can manipulate electoral calendars, they may manipulate election dates to their benefit. Manipulations can happen even in countries with nominally fixed election dates if institutions cannot prevent incumbent machinations. To eliminate this concern, I extend my analysis with quasi-experimental data from Zambia following the untimely deaths of Levy Mwanawasa in 2008 and Michael Sata in 2015. These deaths triggered by-elections, in which election timing was exogenous to agricultural seasons.

My results consistently illustrate a relationship between agricultural seasons and election outcomes. In the Africa-wide and Zambian analyses, there is a curvilinear, inverted-U shape relationship between time from harvest and elections. Initially, as time from harvest increases, so does the expected incumbent vote share and margin of victory. This relationship eventually reverses, however, and additional time from the harvest is associated with poorer election outcomes for the incumbent.

Why do we see these results? To consider the mechanisms linking seasonality to individual voter behavior, I pair my harvest measure with individual survey responses from rounds 5, 6, and 7 of the Afrobarometer. I use three performance measures to see if individual attitudes vary by season: respondents' approval of their government's economic performance, performance on improving living conditions, and performance on keeping down prices. The results illustrate an inverted-u shaped relationship between performance evaluations and time from harvest, mirroring election results. These results suggests that changes in voting behavior could be due to retrospective voting.

There is less evidence for two alternative mechanisms. First, there is no discernible relationship between turnout and time from harvest, auguring against changes in the voter pool from seasonal migration or the opportunity costs of forgoing a day's labor to vote. Additionally, there is no evidence of an association between seasonality and whether respondents identify more with their ethnic or national identity, suggesting it is unlikely that seasonality works through ethnicity-based support networks which households draw from more frequently during certain times of the year.

This empirical strategy has several benefits. First, by using actual election results, it uses real-world data of outcomes in which we are genuinely interested. Second, it combines an analysis of diverse cases from across the continent with exogenously timed elections in Zambia. The Zambian elections allow for a more rigorous test in which the unique nature of the elections can rule out potential confounds. At the same time, the Africa-wide analysis situates results in a richer context and allows for some consideration of external validity and scope conditions. Finally, my analysis moves beyond aggregate measures of election outcomes and explicitly considers which causal mechanisms may be present by using theoretically appropriate individual-level survey responses. Aggregate election results can be convenient and useful but are insufficient for drawing conclusions about individual voter behaviors.

This paper makes several contributions to our understanding of African elections and political life. It uses an original dataset of executive elections by subnational unit and is the most complete dataset of its kind. Furthermore, this paper illustrates how to use a measure of seasonality derived from satellite imagery to answer questions about political outcomes. Substantively, it provides additional evidence of economic and performance voting in sub-Saharan through the novel example of agricultural seasons. Crucially, it illustrates a potential link between agricultural production and retrospective voting. This provides an empirical test of an implication of Sen's (1999) argument for how democracy prevents famines.

1 Environmental Influences on Political Life

Scholars increasingly emphasize the connection between the environment and political outcomes (e.g. Obradovich, 2017; Remmer, 2014), including historical work examining how long-run climactic conditions influence levels of development(e.g Ashraf and Michalopoulos, 2015). Many works more narrowly consider how short-run weather anomalies or shocks (most notably in rainfall) are associated with economic, social, and political outcomes. For example, a rich literature links periods of drought or poor rainfall with higher levels of conflict (Linke et al., 2017; Miguel, Satyanath and Sergenti, 2004).[2] The weather also influences electoral outcomes (Bassi, 2019; Fraga and Hersh, 2011), with election day weather affecting both voters' decisions to vote and for whom they vote.

Although this literature makes many important contributions, there is an overemphasis on the weather as a source of exogenous variation at the expense of long-run seasonal patterns. While short-run anomalies may create attractive empirical opportunities, they overlook structural patterns that condition the political field. Additionally, these accounts often implicitly reduce seasonal or environmental forces to meteorological conditions while postulating variation in agricultural conditions as a mechanism. While a correlation between meteorological and agricultural seasons may exist, these are distinct concepts. Separating these concepts and other forms of seasonal variation will allow researchers to disentangle complex causal processes linking the environment to political outcomes.

[2]See also Schultz and Mankin (2019) for why measured weather anomalies may not be as exogenous as some authors think.

1.1 Agriculture, Economics, and African Elections

Agricultural production has historically been an important component of many African economies. According to the World Bank, most Africans continue to be employed in agriculture, and nearly 60 percent of Africans live in rural communities. In addition to producing food crops, many African countries rely on agricultural commodities such as cocoa, coffee, cotton, rubber, and tea for export earnings.

Given the importance of agriculture to many African economies, it stands to reason that agricultural conditions and economic conditions are tightly intertwined for many voters. Historically, in the pre-colonial period communities overthrew political leaders across the continent after droughts or famines (Isichei, 1997). Today a growing literature applies insights into economic voting developed in western democracies to the African context (Bratton, Bhavnani and Chen, 2012; Lynge and Martinez i Coma, 2022; Rhee, 2021). However, there is surprisingly little work considering whether agricultural conditions and food security influence African voters. Elections are supposed to incentivize politicians to pursue policies promoting food security and avoiding famines (Sen, 1999), yet few studies consider whether agricultural conditions are the voting issue these arguments assume they are.

Accounts of African politics often depict agricultural producers as marginal actors. Bates and Rogerson (1980), for instance, develop a formal model illustrating how governments have incentives to cater to urban consumers at the expense of rural producers. This argument sparked a literature arguing for an "urban bias" in African policymaking. Because urban populations are a larger threat to political stability, regimes attempt to suppress food prices and extract surpluses from the countryside that they can use to buy off urban populations (Bates, 1981).[3] Some do emphasize the role of organized interests in representing the agrarian sector and pressing for state benefits. For example, the structure of the agricultural sector creates incentives for politicians to provide different goods (Bratton, 1987; Widner, 1993,

[3]See van de Walle (1989) for a possible alternative explanation, centering on greater state capacity in cities.

1994). Moreover, these incentives may increase as democracy takes hold across the continent, as the median voter is more likely to work in agriculture, creating electoral incentives to target large groups such as agricultural producers (Bates and Block, 2013).

Politicians can provide a variety of goods and services to support agricultural communities. For instance, after their near-total eradication in the 1990s, agricultural input subsidies are increasingly common across sub-Saharan Africa (Holden, 2019; Jayne et al., 2018). Among other policies, politicians have manipulated producer prices for decades (Bates, 1981; Kasara, 2007), provided extension agents, and funded irrigation projects. These benefits have sparked interest both in how politicians distribute these benefits (Dorward and Chirwa, 2011; Mason, Jayne and Mofya-Mukuka, 2013; Pan and Christiaensen, 2012), and what political effects they might be having (Dionne and Horowitz, 2016).

Finally, there is a lengthy tradition in conflict studies examining the connection between food prices, food security, and violence (Bellemare, 2015; Fjelde, 2015; Koren and Bagozzi, 2016; Rezaeedaryakenari, Landis and Thies, 2020; Smith, 2014). Most accounts consider food scarcity as a source of conflict (Lofchie and Commins, 1982). Communities take up arms to help win control of new resources, allowing them to alleviate food insecurity. More recently, however, Koren (2018) argues conflict is more likely in food-abundant areas, as they are more capable of sustaining armed groups. Some recent research considers seasonality and conflict, finding that seasonal variation in grain prices (Ubilava, Hastings and Atalay, 2022) and labor demands (Guardado and Pennings, 2020) correlate with violence.

2 Conceptualizing Seasonality and Theoretical Mechanisms

In this paper, I focus on a specific aspect of agricultural production: seasonality. Seasonality can refer to several distinct ideas. I am principally interested in agricultural seasonality. In agricultural communities, the year can be divided into distinct, discrete seasons in which households plant their crops, their crops grow, households harvest their crops, and a fallow period until the next planting season.[4] These seasons vary in length and timing by geographic location depending on available rainfall, crop-specific properties, fluctuations in temperature, and sunlight.

2.1 Agricultural Seasonality

Because so much of sub-Saharan Africa remains rural and reliant on agriculture, seasonality plays a vital role in patterning economic and social life. The widespread reliance on rain-fed agriculture means that farmers depend on rain to provide for their crops' water needs. Additionally, air temperature and sunlight are also biological constraints on agricultural production, limiting when crops can be grown.[5] Since rainfall, temperature, and sunlight are subject to seasonal patterns, so is agricultural production. Much of the continent is tied to distinct wet and dry seasons, when the Intertropical Convergence Zone (ITCZ) shifts north or south of the equator with the Earth's orbit. During the wet season, rain is consistent, enabling agricultural production. Rainfall is rare and inconsistent during the dry season, preventing many forms of agricultural production.

These seasonal patterns mean rural communities typically plant crops and harvest crops around the same time every year. Because agricultural production remains an important economic activity, and opportunities for non-farm employment are limited (de Janvry, Duquennois and Sadoulet, 2022), harvests represent a sudden, significant increase in household incomes and well-being. If households grow food crops for household consumption, the food produced in one season must last until the next harvest. If households grow cash crops or sell their product on the market, their harvest proceeds must fund consumption and household expenses until the next harvest.

As the seasons change and communities transition from a fallow post-harvest period to

[4]This is not necessarily exhaustive. For example, there may be a weeding season following planting. Additionally, in select cases continuous, year-round production is possible, eliminating fallow periods.

[5]For example, crops may have genes limiting growth at certain temperatures or levels of available sunlight.

the beginning of the next agricultural season, household savings and food reserves slowly deplete. Food prices increase, at times almost doubling (Gilbert, Christiaensen and Kaminski, 2017; Kaminski, Christiaensen and Gilbert, 2014), as food stocks decrease. While, in principle, interconnected markets should help smooth these price differences, in actuality, many local markets in Africa remain poorly integrated into national and global food markets (Baffes, Kshirsagar and Mitchell, 2017). Often masked by national statistics measured yearly, seasonality forces millions of households into poverty during the year (Dercon and Krishnan, 2000; Dostie, Haggblade and Randriamamonjy, 2002), which they temporarily emerge from following the next harvest.

Agricultural seasonality is distinct from other forms of seasonality people often conflate with one another. Most importantly, meteorological seasonality, or seasonal fluctuations in climatic conditions such as rainfall, overlaps with agricultural seasonality but should be treated as a distinct idea. Agricultural seasonality results from the interaction of crop-specific properties with meteorological conditions in a given place. While meteorological seasonality influences agricultural production, it has other direct effects.[6] For instance, in communities with dirt roads, seasonal rainfall can wash them away, increasing travel costs. During warmer times of the year, household members may be unable to work long hours outside.

In addition to agricultural and meteorological seasonality, a variety of other seasonal patterns shape social life around the world. For instance, festivals and holidays often follow seasonal patterns (e.g. Iyer and Shrivastava, 2018). When communities hold these events to celebrate harvests, they may correlate with agricultural seasonality, although harvest festivals are only a subset of all festivals. Festival seasonality may also influence electoral behaviors. For example, holidays stressing the importance of group unity could prime a community to support co-ethnic candidates.

Agricultural seasonality has a discernible effect on the well-being of agrarian households (Devereux, Sabates-Wheeler and Longhurst, 2012). Historically it has been associated with

[6]Both are distinct from the weather, or short-run fluctuations in meteorological conditions in a given place.

the creation of cash crop economies and colonial policies (Haas, 2021). During lean times of the year, households skip meals, sell assets, and seek the help of family, neighbors, and other local institutions to meet consumption needs (Hill, 1970). In principle, households could attempt to smooth their consumption over the year, reducing seasonality's ill-effects, but prior research shows they largely do not (Fafchamps, Udry and Czukas, 1998; Kazianga and Udry, 2006). Worse still, opportunistic elites act as loan sharks during lean times and take advantage of low prices after harvest to buy surplus crops and then sell those same crops back to households at higher prices later in the year (Fink, Jack and Masiye, 2020; Hill, 1970). Finally, malnutrition follows clear seasonal patterns (Egata, Berhane and Worku, 2013), as households stretch their money and food reserves, decreasing caloric intake and food diversity (Hirvonen, Taffesse and Hassen, 2016).

This leads to my first hypothesis:

H1: A curvilinear, inverted-U-shaped relationship exists between the time from harvest and support for incumbent politicians.

Immediately following harvest, voters are more willing to support incumbent politicians as households process and sell crops. At a certain point, households begin exhausting their harvest proceeds and food reserves. They become less willing to support incumbent politicians until the following harvest approaches.

2.1.1 Mechanisms

I consider three potential mechanisms linking agricultural seasons to election outcomes in this paper. First, agricultural seasonality could induce systematic patterns in how voters evaluate their government's performance. For example, voters may reward incumbents following harvests, as their income and well-being are elevated, and food prices are lower than during other times of the year. This could, in part, be a result of "blind retrospection" in which voters reward or punish politicians for events outside of the politician's control (Achen and Bartels, 2002; Campello and Zucco, 2015; Healy, Malhotra and Mo, 2010), or rational reaction to the inability of many African governments to construct social safety nets to protect agrarian households during lean periods. In this paper, I make no claims about whether changes in performance evaluations should be considered rational.

H2: A curvilinear, inverted-U-shaped relationship exists between the time from harvest and positive evaluations of the incumbent's economic performance.

Second, seasonality could create costs to voting that certain voters are unwilling to shoulder. Farmers may be reluctant to sacrifice a day of labor to vote during specific periods of the agricultural calendar. Rains may wash out dirt roads, making it more difficult for voters or election officials to reach voting centers.[7] Seasonality can induce seasonal migration into urban centers as household members pursue cash-earning opportunities and subsequently are unwilling to pay the travel costs of returning home to vote. These costs could alter the pool of voters, influencing election outcomes through changes in who is voting:

H3: Voter turnout varies with time from harvest.

Third, seasonality could influence the relative strength of local big men and political brokers. During lean periods households are more reliant on these actors for support and may be less willing to cross them at the polls, fearing a loss of social support. This may be particularly acute when these support networks align with politically salient groups, such as ethnic groups. If true, an individual's chosen identification could reflect this.

H4: A curvilinear, U-shaped relationship exists between the time from harvest and identification as a member of a nation instead of a member of an ethnic group.

3 Empirical Analysis

This paper considers the relationship between agricultural seasons and election outcomes. To do this, I use Landsat satellite data to model agricultural seasons, calculate the time

[7] Journalistic accounts often focus on these logistical difficulties believed to be associated with holding elections during the rainy season (e.g. Africa Confidential, 2007, 2013*a*,*b*).

between harvest and an election, and assemble an original dataset of election results by subnational unit. I begin by considering my first hypothesis with all available data across Africa. I then focus on quasi-experimental evidence from two Zambian elections that rule out confounds due to the opportunistic timing of elections by incumbents. Finally, I probe for mechanisms using survey responses from three rounds of the Afrobarometer.

3.1 Measuring Seasons

A challenge this paper faces is accurately measuring agricultural seasons across sub-Saharan Africa. I use satellite data from Landsats 5, 7, and 8 to calculate a normalized difference vegetation index (NDVI) time series for every African subnational unit over thirty years from 1984 to 2014. The NDVI measures how much vegetation exists in a geographic area as satellites continuously record the Earth. The NDVI takes advantage of the fact that plant matter absorbs wavelengths on the visual spectrum but reflects near-infrared wavelengths. Other surfaces, for instance, soil, rocks, or water, either absorb or reflect visual and near-infrared wavelengths.[8] This objectively measures how much vegetation exists in a given region.

This paper is not the first to rely on NDVI estimates to measure agricultural production. Researchers have used NDVI estimates to calculate both agricultural productivity (Dempewolf et al., 2014; Milesi et al., 2010; Tottrup and Rasmussen, 2004) as well as seasonal variation in crop cover (Bellón et al., 2017; Eastman et al., 2013; Kouadio et al., 2014). Similarly, the Food and Agriculture Organization's Global Information and Early Warning System on Food and Agriculture use NDVI estimates to define crop-growing seasons.[9]

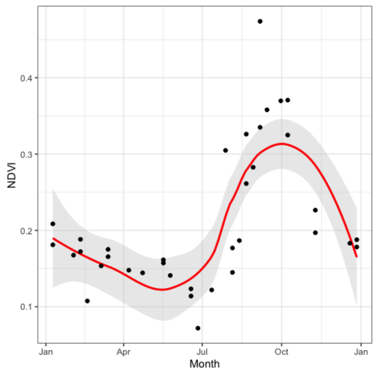
For every African subnational unit, I use Google Earth Engine to calculate the average

[8] Specifically, NDVI is calculated using the following formula:

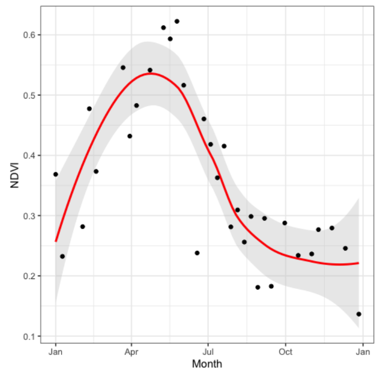
$$\mathrm{NDVI} = \frac{(NIR-Red)}{(NIR+Red}$$

where NIR equals measurements from the near-infrared region, and Red the red visual region.

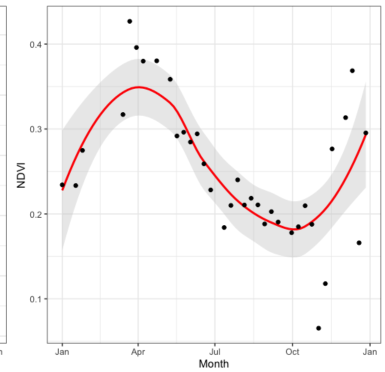
[9] See http://www.fao.org/giews/earthobservation/asis/index_1.jsp.



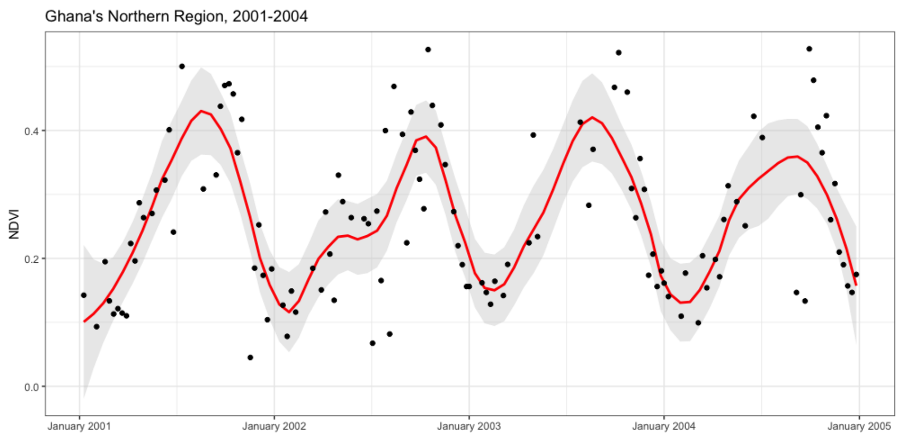
(a) Senegal's Louga Region, 2001



(b) Tanzania's Lindi Region, 1998



(c) Zimbabwe's Midlands Province, 1993



(d) Ghana's Northern Region, 2001-4

Figure 1: Examples of NDVI Yearly Trends

NDVI level for every eight day period with sufficient data between 1984 and 2014. Data may be missing if there is cloud coverage or excessive sand or dust in the atmosphere. I then drop all years with fewer than ten observations and calculate the date of maximum NDVI for each year. Figure 1 shows four examples from across Africa, with observations and a LOESS line of best fit. I join this estimate with election results and count the days between the average maximum NDVI date and election day. For ease of interpretation, I divide this number by 30, creating a measure of "Months from Harvest."

3.2 Seasonality and African Elections

I begin by considering the relationship between agricultural seasons and election results across Africa using an original dataset of executive election results by first-order subnational unit from between 1990 and 2020.[10] This dataset includes information about 145 elections in 32 African countries, broken down by subnational unit.[11] This dataset was made by combining official election results, media reports, and secondary sources. Although it does not contain results from every possible election (See Fridy (2009) for the difficulty in collecting subnational election results in Africa), it improves previous data collection efforts.

I estimate a series of OLS regressions using two-way fixed effects to consider the relationship between agricultural seasons and electoral outcomes. Two-way fixed effects generalize difference-in-difference estimators controlling potential unit and time-invariant confounds. This includes unit-specific differences such as ethnic composition and underlying agricultural conditions and any year-specific exogenous shocks, such as weather shocks or fluctuations in international commodity prices.

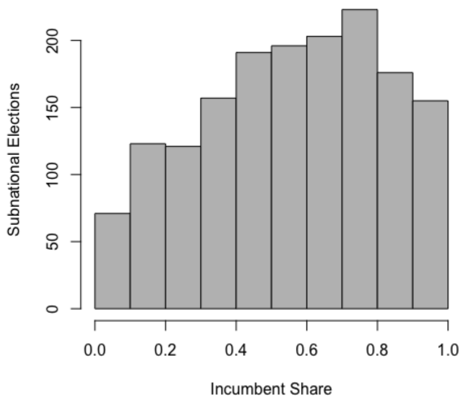
I start with a base model:

$$Y_{imc} = \alpha_i + \beta_1 Months_i + \beta_2 Months_i^2 + \beta_3 X_c + \delta_m \tag{1}$$

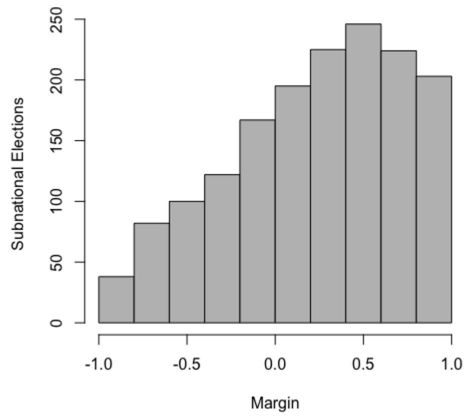
where Y_{imy} is either the share of the vote won by the incumbent executive's political party or the margin between the incumbent candidate and leading challenger. $Months_i$ is a measure of the time between a harvest and the election date for each subnational unit i, while $Months^2$ is a quadratic term to test for a curvilinear relationship between seasons and election outcomes. α_i and δ_m are sub-national unit and year fixed-effects meant to control for time-invariant unobserved confounds, other non-agricultural seasonal effects, and time-

[10] For example, provinces, regions, states, etc.

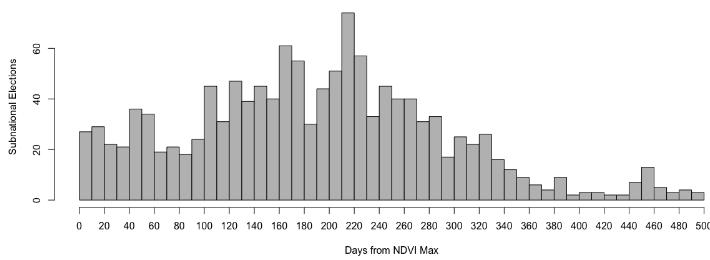
[11] See the Appendix for the list of elections. This dataset primarily consists of presidential election results, including first and second-round results in majoritarian systems, with legislative election results for parliamentary systems.



(a) Incumbent Share by Subnational Unit - Sub-Saharan Africa



(b) Incumbent Margin by Subnational Unit - Sub-Saharan Africa



(c) Days from NDVI Max by Subnational Unit - Sub-Saharan Africa

Figure 2: Descriptive Statistics of Key Variables - Sub-Saharan Africa

specific exogenous shocks. Finally, X_c is a vector of controls, including a country's GDP per capita, its Polity score, the percentage of the country's workforce employed in agriculture, the percentage of a country's GDP from agriculture, and the NDVI value for the region's most recent harvest. These controls are included to help account for situations in which an incumbent may attempt to manipulate an electoral calendar. I cluster all standard errors by subnational unit.

Figure 2 plots election results and an election's time from harvest by subnational unit. African incumbents win, on average, about 55 percent of the vote in a subnational unit, with a margin of victory of about 20 percent. However, there is significant variation in both of these measures. African elections are held, on average, roughly 206 days, or seven months,

Table 1: Subnational Elections by Constituency

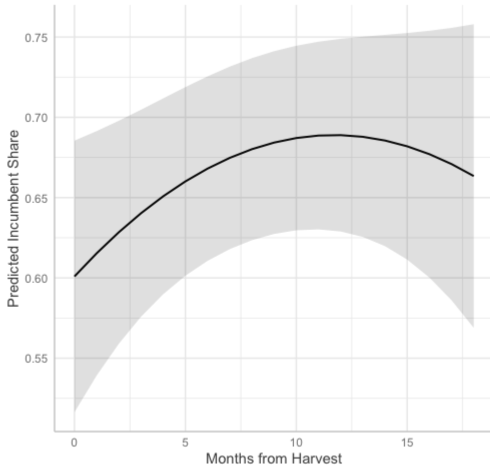
	Incumbent Share		Margin	
	Reduced	Controls	Reduced	Controls
Months from Harvest	0.015*	0.016**	0.031*	0.034**
	(0.007)	(0.006)	(0.012)	(0.012)
Months from Harvest^2	-0.001+	-0.001*	-0.001*	-0.002*
	(0.000)	(0.000)	(0.001)	(0.001)
Harvest NDVI		-0.066		-0.135
		(0.131)		(0.248)
Polity		0.003		0.003
		(0.009)		(0.019)
GDP PC PPP		0.000		0.000
		(0.000)		(0.000)
Pct. Employed Ag.		-0.001		0.000
		(0.003)		(0.006)
Pct. GDP from Ag.		-0.010*		-0.014+
		(0.004)		(0.008)
Num.Obs.	1159	1150	1152	1143
AIC	-1296.4	-1322.0	189.0	161.8
BIC	-1281.2	-1281.6	204.2	202.1
RMSE	0.14	0.14	0.26	0.26
Subnat. Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

Standard Errors Clustered by Subnational Unit
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

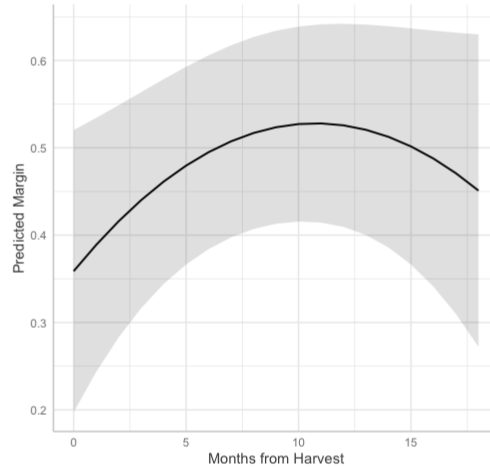
after harvests, but there is, again, meaningful variation in the timing of elections.

3.2.1 Empirical Results

Table 1 shows the results from the Africa-wide analysis. A statistically significant, curvilinear relationship exists between agricultural seasons and election outcomes (see Figure 3). Initially, as time from harvest increases, there is a positive relationship between time from harvest and support for the incumbent. However, over time this relationship weakens and eventually reverses. This relationship holds for both incumbent share and margin and is again substantively significant. Keeping all other covariates constant, holding elections at different points in the agricultural calendar is associated with a nearly 10 percent swing in



(a) Incumbent Share - All Elections



(b) Margin between Incumbent and Challenger - All Elections

Figure 3: Sub-Saharan Africa Predicted Values

the incumbent's vote. This relationship holds after adding controls.

Another way of assessing these results is to see how likely we are to see a relationship as strong or stronger than observed if harvests are randomly assigned.[12] As a robustness check, I randomly generate harvest dates for each subnational unit, calculate months from harvest, and re-estimate models on the new, simulated data. In Figure 4 I repeat this process 10,000 times, plotting simulated T-Values for "Months from Max" and "Months from Max^2."[13] As expected, the results from this procedure suggest that if harvest dates were randomly assigned, there would be no relationship between agricultural seasons and election outcomes on average. Additionally, based on simulated results, there is a less than five percent chance of observing results as strong or stronger in either direction due to random chance alone.

3.3 Quasi-Experimental Evidence from Zambia

One difficulty in analyzing this relationship is non-random election timing. Although most African states have presidential systems, election timing is often malleable and subject to

[12]This procedure is analogous to Fisher's Randomization Inference procedure.

[13]T-Values are calculated by dividing the coefficient estimate by the standard error. Estimated models are identical to the "Controls" models in Table 1.

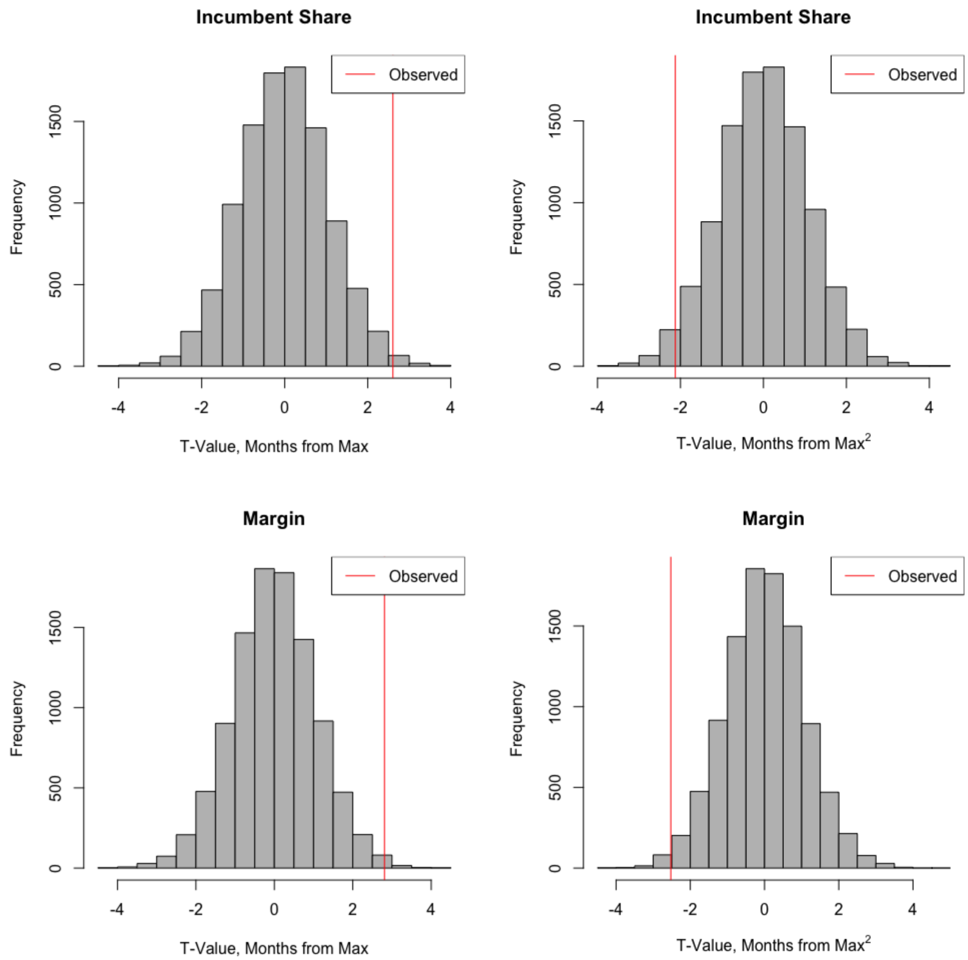


Figure 4: Randomization Inference - All of sub-Saharan Africa

manipulation by incumbent politicians. Among the 145 national elections for which I have data, 27 were either delayed or held before their regularly scheduled date (Hyde and Marinov, 2012). Additionally, 22 elections were either the first competitive election or held after an extra-constitutional change, situations in which the incumbent government may have discretion over election timing.[14]

If national leaders can manipulate electoral calendars for political gain, they may delay elections to more favorable dates.[15] The ability, and incentive, to manipulate election timing

[14] Countries with delayed elections include Angola, Benin, Burundi, Central African Republic, Chad, Côte d'Ivoire, Djibouti, D.R. Congo, Gabon, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Malawi, Niger, Nigeria, Sierra Leone, South Africa, Sudan, Tanzania, Togo, and Zimbabwe.

[15] Accusations to this effect are often made by opposition politicians during delays (e.g. Africa Confidential, 2019).

Table 2: Zambian Presidential By-Elections

President	Date of Death	By-Election Date	Cause of Death
Levy Mwanawasa	19 August 2008	30 October 2008	Stroke
Michael Sata	28 October 2014	20 January 2015	Illness

likely correlate with election outcomes. According to Hyde and Marinov (2012), of the 145 elections for which there I have data, there was reliable pre-election polling for 57 elections. Election dates changed in 33.3 percent of elections with polling data unfavorable to the incumbent, while dates only changed in 15.6 percent of elections with polls favorable to the incumbent. The malleability of election timing in African elections makes it difficult to disentangle the effect of agricultural seasons from the incumbent's anticipated vulnerability. I attempt to remedy this potential problem by focusing on two elections in which we know with certainty their timing was exogenously determined: Zambia's 2008 and 2015 presidential by-elections. Both elections were triggered by the untimely death of the incumbent president and with dates specified by constitutional rules limiting the time between a president's death and a by-election to determine who should finish their term.

3.3.1 Untimely Incumbent Deaths and Early Elections

In the event of the current president's death, the Zambian constitution requires a special by-election within 90 days. This has happened twice in Zambian political history (see Table 2). These deaths create exogenous variation in election timing, eliminating confounds due to the strategic nature of election timing (Bernhard and Leblang, 1999; McClean, 2021; Smith, 2009). Vibrant, multi-party competition marks contemporary Zambian politics, in which three incumbent presidents have lost re-election since 1990. Additionally, according to the World Bank, in 2008 an estimated 71 percent of Zambia's workforce was employed in agriculture, highlighting the importance of agricultural production to Zambian voters.

Following decades of one-party rule, Frederick Chiluba defeated long-time president Kenneth Kaunda in Zambia's first multi-party elections in 1991. After two terms in office, Chiluba was succeeded in 2001 by his vice-president, Levy Mwanawasa. Mwanawasa suffered a mild stroke in April 2006, shortly before his successful 2006 re-election campaign. In June 2008, while attending an African Union meeting, Mwanawasa suffered another stroke and was hospitalized. Two days later, he was medically evacuated to France for treatment. On August 18th, vice president Rupiah Banda announced that Mwanawasa's condition was worsening. He passed away the next day at the age of 59. On October 30th, 72 days after Mwanawasa's death, Zambian voters elected Banda to finish Mwanawasa's term.

Banda defeated Michael Sata of the Patriotic Front but would lose a rematch to Sata in Zambia's 2011 election. Santa was an experienced politician, holding political appointments during the Kaunda years and several Ministry-level appointments during Chiluba's presidency. Throughout 2014 rumors swirled that Sata's health was in poor and deteriorating condition, as the ordinarily extroverted politician shied away from public appearances. Then, on October 19th, days before Zambia's 50th anniversary of independence, Sata left for London in what his office described as a medical check-up. He passed away on October 28th from an undisclosed illness at 77.

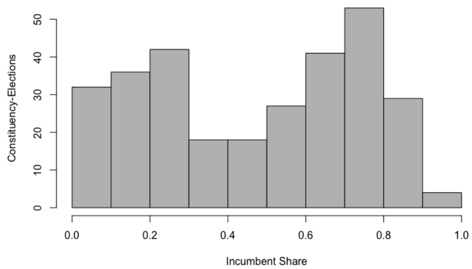
On January 20th, 2015, 84 days following Sata's death, Zambian voters went to the polls to choose who would finish Sata's term. Santa's political party, the Patriotic Front, nominated Edgar Lungu, Sata's Defense Minister, who would eventually prevail over Hakainde Hichilema of the United Party for National Development.[16]

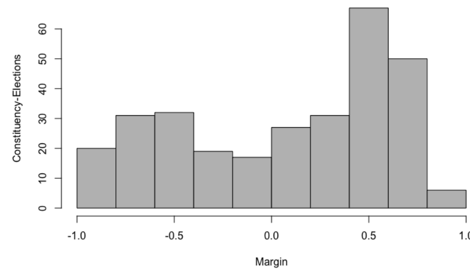
To consider the relationship between agricultural seasons and election outcomes in Zambia, I again estimate a series of two-way fixed-effects OLS regressions, including subnational unit and time-specific fixed effects:

$$Y_{cy} = \alpha_c + \beta_1 Months_c + \beta_2 Months_c^2 + \tau_y \tag{2}$$

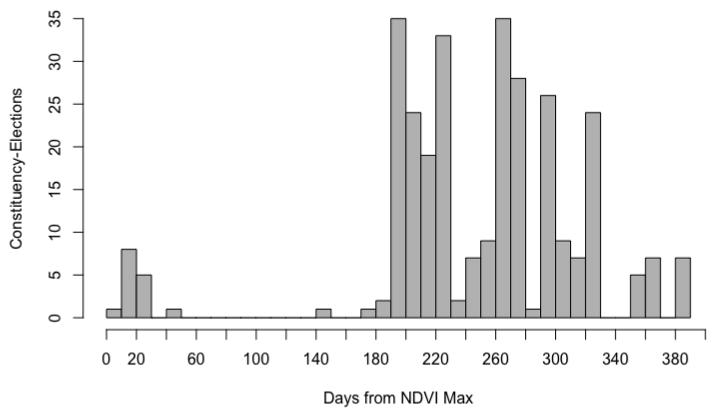
where Y_{cpy} is an electoral outcome, either the share of the vote won by the nominee of the

[16] Sata Vice President, Guy Scott, served as interim president but did not stand in the election. Scott was the first white head of state in sub-Saharan Africa since apartheid.





(a) Incumbent Share by Constituency (b) Incumbent Margin by Constituency



(c) Days from NDVI Max by Constituency

Figure 5: Descriptive Statistics of Key Variables - Zambia

incumbent president's political party or the margin between the incumbent party's nominee and the leading challenger, for each of Zambia's 150 electoral constituencies.[17] $Months_c$ measures months from harvest, measured by months from average maximum NDVI date, and $Months_c^2$ is a quadratic term to test for a curvilinear relationship. α_c are constituency fixed-effects, and τ_y are year fixed-effects. Including constituency and year fixed-effects means coefficient estimates can be interpreted as difference-in-difference estimates.

I also estimate models including both fixed-effects and a lagged dependent variable. However, we should interpret these models carefully as constituency fixed-effects effects correlate with lagged dependent variables, resulting in inconsistent estimates. All models include standard errors clustered by constituency.

[17]Election results are taken from the Electoral Commission of Zambia's website.

Table 3: Zambian Presidential Elections by Constituency

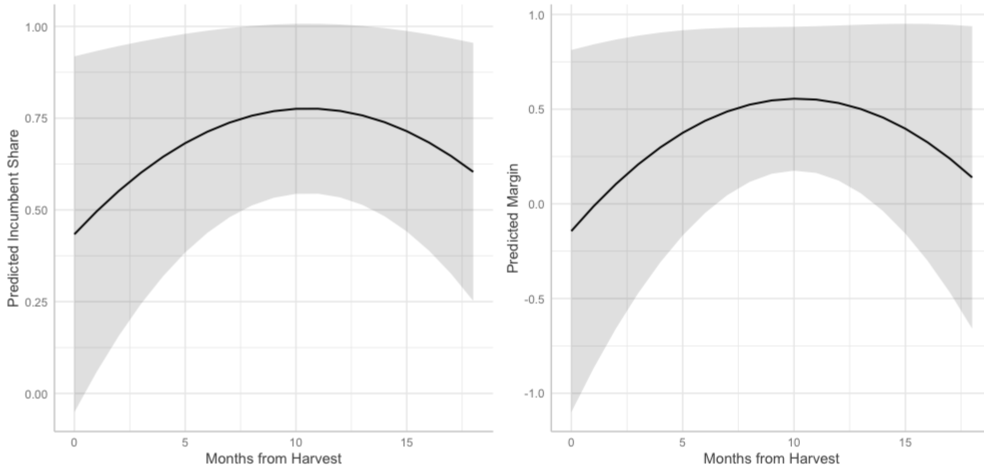
	Incumbent	Margin	Incumbent	Margin
Months from Harvest	0.067*	0.142*	0.062**	0.159***
	(0.028)	(0.060)	(0.017)	(0.040)
Months from Harvest^2	-0.003**	-0.007**	-0.003***	-0.008***
	(0.001)	(0.002)	(0.001)	(0.001)
Lagged DV			0.120	-0.390
			(0.565)	(0.760)
Num.Obs.	300	300	300	300
AIC	-112.3	399.9	-111.4	398.3
BIC	-97.5	414.7	-92.9	416.9
RMSE	0.20	0.46	0.20	0.46
Constituency FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

Standard Errors Clustered by Province-Year
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5 plots the frequency of my dependent variables and time from harvest by constituency. In the election results, we see two peaks, corresponding to constituencies in which the incumbent party won between 60 and 80 percent of the vote and constituencies where they only won between 10 and 20 percent of the vote. Most elections occur between six and ten months after a constituency's harvest.

3.3.2 Empirical Results

Table 3 shows coefficient estimates from OLS regression models probing the relationship between agricultural seasons and election results. As expected, these estimates show a clear, curvilinear relationship between months from harvest and the share of the vote won by the incumbent party's candidate, and the margin between the incumbent party's candidate and leading challenger. As time from harvest increases, incumbents can first expect to see more favorable results. However, after about six months, this effect reverses, and additional time between harvest and an election is associated with poorer election outcomes. Figure 6 plots the predicted share of the vote and margin, graphically illustrating this result. This effect is



(a) Incumbent Share - All Zambian Elections

(b) Margin between Incumbent and Challenger - All Zambian Elections

Figure 6: Zambia Predicted Values

substantively as well as statistically significant. The incumbent's vote share can vary by as much as 25 percent between seasonal extremes.

As a robustness check, I re-estimate these results using randomly generated harvest dates. I calculate the time between these randomly generated harvest dates and elections and re-estimate my main results. I run 10,000 simulations, plot associated T-Values, and compare them with the observed results (see Figure 7). As expected, simulated results show, on average, no relationship between agricultural seasons and election outcomes. Moreover, there is a less than 10 percent chance of observing a relationship as strong or stronger between Months from Harvest and either incumbent vote share or margin if harvest dates were randomly assigned.

One potential challenge to these results is that voters might be reacting to the death of the incumbent president by voting for the incumbent party's candidate out of a sense of sympathy. However, there are two reasons to discount this potential threat. First, every voter is exposed to this possible effect, making it unlikely to explain variation in election results. Second, suppose we assume that some voters, for example, those of the incumbent's party or home region, are particularly prone to this effect. In that case, any sympathy effect

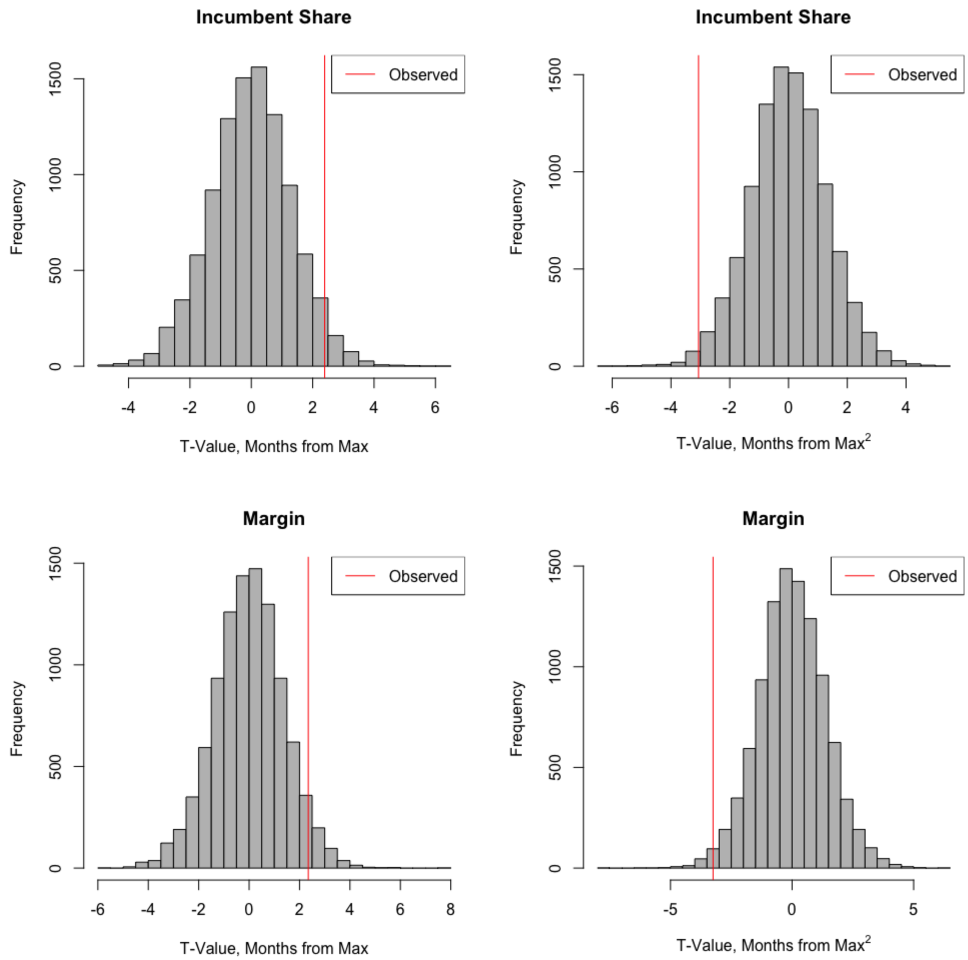


Figure 7: Randomization Inference - Zambia

from the incumbent's death should be soaked up by constituency fixed effects.

3.4 Mechanisms Linking Seasonality and Elections

What explains this association between agricultural seasons and election outcomes? I briefly consider three potential mechanisms: 1.) Seasonal variation in incumbent performance evaluations, 2.) Changes to the pool of voters, and 3.) Seasonal fluctuations in salient political identities due to reliance on support networks.

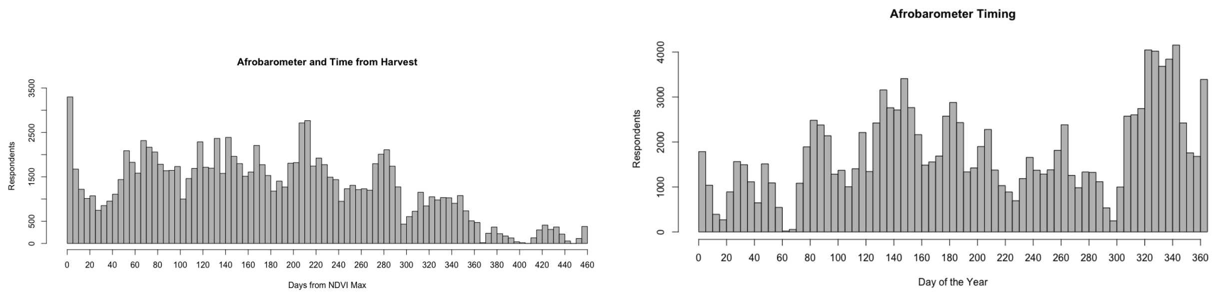


Figure 8: Afrobarometer Timing, Rounds 5, 6, and 7 Pooled

3.4.1 Accountability and Retrospective Voting

I first consider the possibility that changes in election outcomes result from changes in performance evaluations tied to agricultural seasons. To assess this possibility, I use individual-level survey responses from rounds 5,6 and 7 of the Afrobarometer. Altogether there are over 120,000 responses from 30 countries in these rounds.[18] Using the enumerator recorded interview date, I pair Afrobarometer responses with my measure of maximum NDVI date to create a "Months from Harvest" variable. Figure 8 shows survey responses by days from harvest and date of the year (where 0 equals January 1st). These plots show substantial variation in Afrobarometer survey timing according to the time of year and agricultural season in which the interview is conducted.

During different times of the agricultural calendar, farming households may be more or less willing to reward or sanction incumbent politicians at the ballot box. This could be a rational reaction to the lack of social safety nets or other public policies to alleviate seasonality's deleterious effects or could be an example of "blind retrospection" in which voters hold politicians accountable for factors beyond their control. According to this logic, politicians will receive more favorable performance evaluations following harvests, worsening as the agricultural calendar progresses.

To consider this mechanism, I rely on three measures of incumbent economic performance

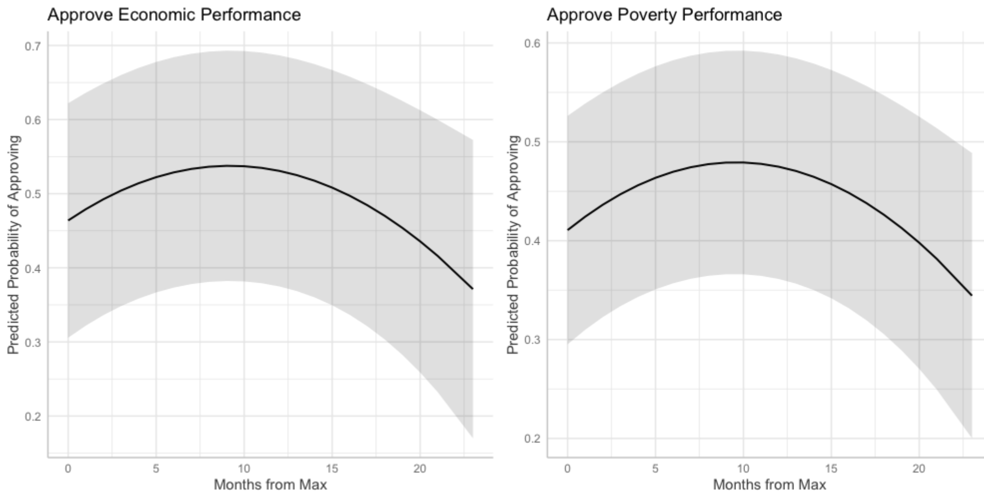
[18]See the Appendix for a complete list of country-rounds, sample sizes, and survey dates for included rounds.

Table 4: Seasonality and the Afrobarometer - OLS

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.039***	0.022**	0.018*	0.003
	(0.009)	(0.008)	(0.008)	(0.004)
Months from Harvest^2	-0.002***	-0.001*	-0.001+	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Harvest NDVI	0.225+	0.284*	0.507***	0.062
	(0.129)	(0.113)	(0.113)	(0.059)
Rural	0.008	-0.008	0.006	0.020**
	(0.015)	(0.012)	(0.013)	(0.006)
Age	0.000	0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employed	-0.003	0.009	-0.015+	-0.020***
	(0.011)	(0.009)	(0.009)	(0.005)
Female	-0.038***	-0.019***	-0.017**	0.022***
	(0.006)	(0.006)	(0.006)	(0.003)
Discuss Pol.	-0.006	0.002	0.005	-0.008**
	(0.006)	(0.005)	(0.005)	(0.003)
Constant	1.301***	1.297***	1.279***	0.966***
	(0.166)	(0.139)	(0.132)	(0.062)
Num.Obs.	108298	110280	109765	105186
R2	0.141	0.126	0.122	0.129
AIC	363475.3	387746.5	400975.5	625692.8
BIC	3353948.7	3476598.4	3449985.2	3238906.0
RMSE	0.88	0.85	0.82	0.47
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included
Standard Errors Clustered by PSU
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

from the Afrobarometer. The first is whether the respondent believes the government handles the economy fairly or very well. Second, a measure of whether the respondent thinks the government does fairly or very well at improving the living standards of the poor. Third, a measure of whether the respondent believes the government does fairly or very well at keeping consumer prices down. In my main results, I keep each variable as an ordinal measure but repeat my analysis in the appendix with dummy variables as dependent variables. These questions capture different elements of seasonality that might influence performance evalua-



(a) Approve of Economic Performance (b) Approve of Poverty Performance

Figure 9: Afrobarometer Predicted Probabilities

tions. Finally, I control respondents' urban/rural location, age, employment status, gender, and whether they discuss politics. I estimate OLS models with these dependent variables among all respondents Africa-wide. Each model includes sub-national unit, month, year, and month-in-year (e.g., April 2014, October 2009) fixed effects. Finally, I cluster standard errors by the primary sampling unit.

Table 4 shows coefficient estimates from this analysis. Among all respondents, there is an apparent relationship between agricultural seasons and performance evaluations related to the economy, improving the living standards of the poor, and keeping prices down. These results resemble the inverted U-shape seen earlier, where performance evaluations initially increase with Months from Harvest before reversing later in the calendar (See 9).

3.4.2 Migration, Labor and the Costs of Voting

Next, I consider the possibility that changes in election outcomes result from changes in the voter pool. Voting is not a costless endeavor; the costs associated with voting may vary by agricultural season. This could be due to the opportunity costs associated with voting. Labor may be critical at certain times in the agricultural calendar (e.g., planting, weeding, harvesting), and forgoing a day's labor to queue at the polls is more costly than during

Table 5: Seasonality and Turnout

	All Africa	Zambia
Months from Harvest	-0.006	-0.007
	(0.004)	(0.004)
Months from Harvest^2	0.000	-0.000
	(0.000)	(0.000)
Harvest NDVI	-0.002	-0.055
	(0.082)	(0.115)
Num.Obs.	846	300
AIC	-2361.1	-795.2
BIC	-2342.2	-780.4
RMSE	0.06	0.06
Region FEs	Yes	Yes
Year FEs	Yes	Yes

Zambia Models SEs Clustered by Constituency
Africa Model SEs Clustered by Subnational Unit
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

other periods in the agricultural calendar. Additionally, there could be costs associated with voting that vary during the year. For example, agricultural workers may migrate to urban centers during fallow periods to pursue cash-earning opportunities, and the transportation costs of returning to their home village to vote may be prohibitive. Voters in especially rural communities may find it difficult to travel to the polls during the rainy season. These costs may fall unevenly. For instance, it could be that workers of a particular gender are expected to perform certain types of labor, or younger workers may be more likely to migrate to urban centers. These potential costs of voting could correlate with age, gender, income, and other variables that could, in turn, correlate with support for incumbent politicians for various reasons. In this way, agricultural seasons would indirectly affect election outcomes by influencing who participates in an election.

I examine the relationship between Months from Harvest and turnout to test this possibility. If there are changes in the pool of voters, this should be reflected in different turnout rates. As seen in Table 5, however, there is no relationship between seasonality and turnout in the Africa-wide or Zambia sample. This suggests that the observed seasonality results are unlikely to be a product of variation in the voter pool.

3.4.3 Support Networks and Political Identification

The final mechanism I consider is whether seasonality induces changes in how individuals relate to different groups. In particular, as households may be more reliant on family, friends, and coethnics for support during lean times, they may be less likely to vote for an incumbent of another group. This reluctance could be in fear of losing out on potential support or simply because they feel more attached to their group during vulnerable periods. This could result in larger vote shares for incumbents following harvests as households feel freer to cross ethnic boundaries and vote for an incumbent of another group.

I test for this possibility by again using a question drawn from the Afrobarometer, which asks respondents whether they identify more as a member of an ethnic group or a member of a nation (e.g., as a Kikuyu or as a Kenyan). While an imperfect test of this mechanism, seasonal variation in this measure could indicate that ethnic salience varies by season. The estimates in Table 4 show no evidence supporting this supposition.

4 Conclusion

Despite significant research in development economics and public health, political science has been slow to consider potential seasonal effects on electoral outcomes. This paper begins to fill this gap by considering whether African incumbents do better in elections held after harvests and, if so, why.

Starting with an analysis of election outcomes across Africa, this paper shows a curvilinear relationship between time from harvest and support for incumbent politicians. Initially, time from harvest is associated with better results for the incumbent. Eventually, this relationship reverses, and more time from harvest is associated with poorer electoral outcomes for the incumbent. I replicate these results in a second analysis of quasi-experimental evidence from two Zambian by-elections triggered by the untimely death of incumbent presidents. A subsequent analysis of Afrobarometer survey responses indicates a potential mechanism explaining this result: retrospective voting. Not only are aggregate election outcomes varying by season, but so are individual evaluations of government performance.

These results offer lessons for several audiences. First, African policymakers should craft policies to counteract seasonality's harmful effects, particularly those interested in winning re-election. Doing so may be a boon for the re-election chances. Similarly, researchers of African politics should account for potential seasonal effects in their research, particularly when collecting data. When a survey or field experiment goes into the field may interact with agricultural seasonality in unexpected ways, patterning results.

For researchers, these results improve our understanding of the relationship between the environment and social and political outcomes in Africa and economic voting. Researchers are increasingly interested in how the environment influences political outcomes and vice versa. This interest is only growing with the threat of climate change. While climate scientists acknowledge the growing risk of disturbances in agricultural seasons related to climate change, we know little about how agricultural seasons influence political outcomes absent any changes to them. This paper fills this gap and represents a starting point for future research examining seasonality. Finally, it is often thought that African governments should be responsive to popular demands for food security and improved agricultural conditions. However, this is predicated on the idea that African voters are willing to cast their ballots based on these issues. This idea has not been extensively tested, but this paper provides evidence to support the idea that agricultural performance is a voting issue for many Africans.

The results presented here support the idea that a relationship exists between agricultural seasonality and election outcomes across Africa. However, the causal chains linking environmental forces and political outcomes are complex and subject to potential moderators and scope conditions. Future research should focus on more specific causal processes and consider how seasonality influences social and political relationships in agrarian African communities. Finally, there are a variety of political outcomes, from voter behavior to clientelism and distributive politics, to other forms of political participation that similarly could be subject to seasonal variation.

References

Achen, Christopher H. and Larry M. Bartels. 2002. Blind Retrospection: Electoral Responses to Drought, Flu, and Shark Attacks. In *Annual Meeting of the American Political Science Association*. Boston, MA: .

Africa Confidential. 2007. “Personal not proportional.”.

Africa Confidential. 2013*a*. “No princes on the ballot.”.

Africa Confidential. 2013*b*. “The rush to vote.”.

Africa Confidential. 2019. “Drama in the delay.”.

Ashraf, Quamrul and Stelios Michalopoulos. 2015. “Climatic Fluctuations and the Diffusion of Agriculture.” *Review of Economics and Statistics* .

Baffes, John, Varun Kshirsagar and Donald Mitchell. 2017. “What Drives Local Food Prices? Evidence from the Tanzanian Maize Market.” *The World Bank Economic Review* .

Bassi, Anna. 2019. “Weather, Risk, and Voting: An Experimental Analysis of the Effect of Weather on Vote Choice.” *Journal of Experimental Political Science* 6(1):17–32.

Bates, Robert H. 1981. *Markets and States in Tropical Africa: the Political Basis of Agricultural Policies*. Berkeley, CA: University of California Press.

Bates, Robert H. and Steven A. Block. 2013. “Revisiting African Agriculture: Institutional Change and Productivity Growth.” *The Journal of Politics* 75(2):372–384.

Bates, Robert H. and William P. Rogerson. 1980. “Agriculture in Development: A Coalitional Analysis.” *Public Choice* 35(5):513–527.

Bellemare, Marc F. 2015. “Rising Food Prices, Food Price Volatility, and Social Unrest.” *American Journal of Agricultural Economics* 97(1):1–21.

Bellón, Beatriz, Agnès Bégué, Danny Lo Seen, Claudio Aparecido De Almeida and Margareth Simões. 2017. “A Remote Sensing Approach for Regional-Scale Mapping of Agricultural Land-Use Systems Based on NDVI Time Series.” *Remote Sensing* 9(6):600.

Bernhard, William and David Leblang. 1999. “Democratic Institutions and Exchange-Rate Commitments.” *International Organization* 53(1):71–97.

Bratton, Michael. 1987. “The Comrades and the Countryside: The Politics of Agricultural Policy in Zimbabwe.” *World Politics* 39(2):174–202.

Bratton, Michael, Ravi Bhavnani and Tse-Hsin Chen. 2012. “Voting intentions in Africa: ethnic, economic or partisan?” *Commonwealth & Comparative Politics* 50(1):27–52.

Campello, Daniela and Cesar Zucco. 2015. “Presidential Success and the World Economy.” *The Journal of Politics* 78(2):589–602.

de Janvry, Alain, Claire Duquennois and Elisabeth Sadoulet. 2022. "Labor calendars and rural poverty: A case study for Malawi." *Food Policy* 109:102255.

Dempewolf, Jan, Bernard Adusei, Inbal Becker-Reshef, Matthew Hansen, Peter Potapov, Ahmad Khan and Brian Barker. 2014. "Wheat Yield Forecasting for Punjab Province from Vegetation Index Time Series and Historic Crop Statistics." *Remote Sensing* 6(10):9653–9675.

Dercon, Stefan and Pramila Krishnan. 2000. "Vulnerability, seasonality and poverty in Ethiopia." *The Journal of Development Studies* 36(6):25–53.

Devereux, Stephen, Rachel Sabates-Wheeler and Richard Longhurst, eds. 2012. *Seasonality, rural livelihoods, and development*. New York, NY: Earthscan.

Dionne, Kim Yi and Jeremy Horowitz. 2016. "The Political Effects of Agricultural Subsidies in Africa: Evidence from Malawi." *World Development* 87:215–226.

Dorward, Andrew and Ephraim Chirwa. 2011. "The Malawi agricultural input subsidy programme: 2005/06 to 2008/09." *International Journal of Agricultural Sustainability* 9(1):232–247.

Dostie, B., S. Haggblade and J. Randriamamonjy. 2002. "Seasonal poverty in Madagascar: magnitude and solutions." *Food Policy* 27(5):493–518.

Eastman, J. Ronald, Florencia Sangermano, Elia A. Machado, John Rogan and Assaf Anyamba. 2013. "Global Trends in Seasonality of Normalized Difference Vegetation Index (NDVI), 1982–2011." *Remote Sensing* 5(10):4799–4818.

Egata, Gudina, Yemane Berhane and Alemayehu Worku. 2013. "Seasonal variation in the prevalence of acute undernutrition among children under five years of age in east rural Ethiopia: a longitudinal study." *BMC Public Health* 13:864.

Fafchamps, Marcel, Christopher Udry and Katherine Czukas. 1998. "Drought and saving in West Africa: are livestock a buffer stock?" *Journal of Development Economics* 55(2):273–305.

Fink, Günther, B. Kelsey Jack and Felix Masiye. 2020. "Seasonal Liquidity, Rural Labor Markets, and Agricultural Production." *American Economic Review* 110(11):3351–3392.

Fjelde, Hanne. 2015. "Farming or Fighting? Agricultural Price Shocks and Civil War in Africa." *World Development* 67:525–534.

Fraga, Bernard and Eitan Hersh. 2011. "Voting Costs and Voter Turnout in Competitive Elections." *Quarterly Journal of Political Science* 5(4):339–356.

Fridy, Kevin S. 2009. "Africa's disappearing election results : why announcing the winner is simply not enough." *Journal of African Elections* 8(2):88–101.

Gilbert, Christopher L., Luc Christiaensen and Jonathan Kaminski. 2017. "Food price seasonality in Africa: Measurement and extent." *Food Policy* 67:119–132.

Guardado, Jenny and Steven Pennings. 2020. The Seasonality of Conflict. Working Paper World Bank Washington, D.C.: .

Haas, Michiel de. 2021. "The Failure of Cotton Imperialism in Africa: Seasonal Constraints and Contrasting Outcomes in French West Africa and British Uganda." *The Journal of Economic History* pp. 1–39.

Healy, Andrew J., Neil Malhotra and Cecilia Hyunjung Mo. 2010. "Irrelevant events affect voters' evaluations of government performance." *Proceedings of the National Academy of Sciences* 107(29):12804–12809.

Hill, Polly. 1970. *Studies in Rural Capitalism in West Africa*. Cambridge, U.K.: Cambridge University Press.

Hirvonen, Kalle, Alemayehu Seyoum Taffesse and Ibrahim Worku Hassen. 2016. "Seasonality and household diets in Ethiopia." *Public Health Nutrition* 19(10):1723–1730.

Holden, Stein T. 2019. "Economics of Farm Input Subsidies in Africa." *Annual Review of Resource Economics* 11(1):501–522.

Hyde, Susan D. and Nikolay Marinov. 2012. "Which Elections Can Be Lost?" *Political Analysis* 20(2):191–210.

Isichei, Elizabeth. 1997. *A History of African Societies to 1870*. Cambridge, U.K.: Cambridge University Press.

Iyer, Sriya and Anand Shrivastava. 2018. "Religious riots and electoral politics in India." *Journal of Development Economics* 131:104–122.

Jayne, Thomas S., Nicole M. Mason, William J. Burke and Joshua Ariga. 2018. "Review: Taking stock of Africa's second-generation agricultural input subsidy programs." *Food Policy* 75:1–14.

Kaminski, Jonathan, Luc Christiaensen and Christopher L. Gilbert. 2014. The end of seasonality ? new insights from Sub-Saharan Africa. Policy Research Working Paper Series 6907 The World Bank.

Kasara, Kimuli. 2007. "Tax Me If You Can: Ethnic Geography, Democracy, and the Taxation of Agriculture in Africa." *American Political Science Review* 101(1):159–172.

Kazianga, Harounan and Christopher Udry. 2006. "Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso." *Journal of Development Economics* 79(2):413–446.

Koren, Ore. 2018. "Food Abundance and Violent Conflict in Africa." *American Journal of Agricultural Economics* 100(4):981–1006.

Koren, Ore and Benjamin E. Bagozzi. 2016. "From global to local, food insecurity is associated with contemporary armed conflicts." *Food Security* 8(5):999–1010.

Kouadio, Louis, Nathaniel K. Newlands, Andrew Davidson, Yinsuo Zhang and Aston Chipanshi. 2014. "Assessing the Performance of MODIS NDVI and EVI for Seasonal Crop Yield Forecasting at the Ecodistrict Scale." *Remote Sensing* 6(10):10193–10214.

Linke, Andrew M., Frank D. W. Witmer, John O'Loughlin, J. Terrence McCabe and Jaroslav Tir. 2017. "Drought, Local Institutional Contexts, and Support for Violence in Kenya." *Journal of Conflict Resolution* .

Lofchie, Michael F. and Stephen K. Commins. 1982. "Food Deficits and Agricultural Policies in Tropical Africa." *The Journal of Modern African Studies* 20(1):1–25.

Lynge, Halfdan and Ferran Martinez i Coma. 2022. "The effect of economic downturns on voter turnout in Africa." *Electoral Studies* 76:102456.

Mason, Nicole M., T. S. Jayne and Rhoda Mofya-Mukuka. 2013. "Zambia's input subsidy programs." *Agricultural Economics* 44(6):613–628.

McClean, Charles T. 2021. "The Element of Surprise: Election Timing and Opposition Preparedness." *Comparative Political Studies* .

Miguel, Edward, Shanker Satyanath and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112(4):725–753.

Milesi, Cristina, Arindam Samanta, Hirofumi Hashimoto, K. Krishna Kumar, Sangram Ganguly, Prasad S. Thenkabail, Ashok N. Srivastava, Ramakrishna R. Nemani and Ranga B. Myneni. 2010. "Decadal Variations in NDVI and Food Production in India." *Remote Sensing* 2(3):758–776.

Obradovich, Nick. 2017. "Climate change may speed democratic turnover." *Climatic Change* 140(2):135–147.

Pan, Lei and Luc Christiaensen. 2012. "Who is Vouching for the Input Voucher? Decentralized Targeting and Elite Capture in Tanzania." *World Development* 40(8):1619–1633.

Remmer, Karen L. 2014. "Exogenous Shocks and Democratic Accountability: Evidence From the Caribbean." *Comparative Political Studies* 47(8):1158–1185. Publisher: SAGE Publications Inc.

Rezaeedaryakenari, Babak, Steven T. Landis and Cameron G. Thies. 2020. "Food price volatilities and civilian victimization in Africa." *Conflict Management and Peace Science* 37(2):193–214.

Rhee, Inbok. 2021. "Economic Perception to Political Performance Evaluation: Establishing Precursors to Economic Voting in Africa." *Political Research Quarterly* 74(1):131–147.

Schultz, Kenneth A. and Justin S. Mankin. 2019. "Is Temperature Exogenous? The Impact of Civil Conflict on the Instrumental Climate Record in Sub-Saharan Africa." *American Journal of Political Science* 63(4):723–739.

Sen, Amartya. 1999. *Development as Freedom*. Oxford, U.K.: Oxford University Press.

Smith, Alastair. 2009. *Election Timing*. Cambridge, U.K.: Cambridge University Press.

Smith, Todd Graham. 2014. "Feeding unrest: Disentangling the causal relationship between food price shocks and sociopolitical conflict in urban Africa." *Journal of Peace Research* 51(6):679–695.

Tottrup, Christian and Michael Schultz Rasmussen. 2004. "Mapping long-term changes in savannah crop productivity in Senegal through trend analysis of time series of remote sensing data." *Agriculture, Ecosystems & Environment* 103(3):545–560.

Ubilava, David, Justin V. Hastings and Kadir Atalay. 2022. "Agricultural Windfalls and the Seasonality of Political Violence in Africa.".

van de Walle, Nicolas. 1989. "Rice Politics in Cameroon: State Commitment, Capability, and Urban Bias." *The Journal of Modern African Studies* 27(4):579–599.

Widner, Jennifer A. 1993. "The origins of agricultural policy in Ivory Coast 1960–86." *The Journal of Development Studies* 29(4):25–59.

Widner, Jennifer A. 1994. "Single Party States and Agricultural Policies: The Cases of Ivory Coast and Kenya." *Comparative Politics* 26(2):127–147.

Appendix A: Data Descriptions

A.1 Elections

Country	Election
Angola	1992(P), 2008(L), 2012(L), 2017(L)
Benin	1991(R1/R2), 1996(R1/R2), 2001(R1/R2), 2011(P), 2016(R1/R2)
Burkina Faso	2005(P), 2010(P)
Burundi	1993(P), 2015(P), 2020(P)
Cameroon	1992(P), 2011(P) , 2018(P)
Côte d'Ivoire	2010(R1/R2), 2015(P)
Djibouti	1999(P)
Congo, D.R.	2006(R1/R2), 2011(P)
Congo, R.	1992(R1)
Gabon	2016(P)
Gambia	1992(P), 1996(P), 2001(P), 2006(P), 2011(P), 2016(P)
Ghana	1992(P), 1996(P), 2000(P), 2004(P), 2008(P), 2012(P), 2016(P)
Guinea-Bissau	1996(R1/R2), 1999(R2), 2009(R1/R2), 2019(R1)
Kenya	1992(P), 1997(P), 2002(P), 2007(P), 2013(P), 2017(P)
Liberia	2011(R1/R2), 2017(R1/R2)
Madagascar	2001(P), 2006(P), 2018(R1)
Malawi	1994(P), 1999(P), 2004(P), 2009(P), 2014(P), 2019(P), 2020(P)
Mali	2002(R2), 2007(P), 2018(R2)
Mozambique	1994(P), 1999(P), 2004(P), 2009(P), 2014(P), 2019(P)
Namibia	1994(P), 1999(P), 2004(P), 2009(P)
Niger	1993(R1/R2), 1996(P)
Nigeria	1999(P), 2003(P), 2011(P), 2015(P), 2019(P)
Rwanda	2003(P), 2010(P), 2017(P)
Senegal	1993(P), 2000(R1/R2), 2007(P), 2012(R1/R2), 2019(P)
Sierra Leone	1996(R1/R2), 2002(P), 2007(R1/R2), 2012(P), 2018(R1/R2)
South Africa	1994(L), 1999(L), 2004(L), 2009(L), 2014(L), 2019(L)
Sudan	2010(P)
Tanzania	1995(P), 2005(P), 2010(P), 2015(P)
Togo	1993(P), 1998(P), 2003(P), 2010(P), 2015(P), 2020(P)
Uganda	1996(P), 2001(P), 2006(P), 2011(P), 2016(P)
Zambia	1991(P), 1996(P), 2001(P), 2006(P), 2008(P), 2011(P), 2015(P), 2016(P)
Zimbabwe	2002(P), 2008(R1/R2), 2013(P), 2018(P)
Note: L = Legislative, P = Presidential, R1/R2 = Presidential Round 1/Round 2	

A.2 Afrobarometer Surveys

Country	Field Dates	Sample Size
	Round 5	44389
Benin	11/16/2011 - 12/06/2011	1200
Botswana	6/30/2012 - 7/12/2012	1200
Burkina Faso	12/03/2012 - 12/17/2012	1200
Burundi	11/28/2012 - 12/10/2012	1200
Cameroon	3/17/2013 - 4/02/2013	1200
Cote d'Ivorie	3/11/2013 - 3/26/2013	1200
Ghana	5/08/2012 - 5/27/2012	2400
Guinea	3/23/2013 - 4/12/2013	1200
Kenya	11/02/2011 - 11/29/2011	2399
Lesotho	11/26/2012 - 12/29/2012	1197
Liberia	6/25/2012 - 7/25/2012	1199
Madagascar	3/11/2013 - 4/07/2013	1200
Malawi	6/04/2012 - 7/01/2012	2407
Mali	12/16/2012 - 1/10/2013	1200
Mozambique	11/17/2012 - 12/09/2012	2400
Namibia	11/19/2012 - 12/09/2012	1200
Niger	3/31/2013 - 4/15/2013	1199
Nigeria	10/30/2012 - 1/19/2013	2400
Senegal	2/18/2013 - 3/02/2013	1200
Sierra Leone	6/23/2012 - 7/17/2012	1190
South Africa	10/20/2011 - 11/30/2011	2399
Sudan	2/13/2013 - 2/23/2013	1199
Swaziland	5/22/2013 - 6/04/2013	1200
Tanzania	5/28/2013 - 6/30/2013	2400
Togo	12/17/2012 - 12/29/2012	1200
Uganda	12/02/2011 - 2/28/2012	2400
Zambia	1/21/2012 - 2/29/2013	1200
Zimbabwe	7/16/2012 - 7/30/2012	2400

Country	Field Dates	Sample Size
	Round 6	45541
Benin	5/25/2014 - 6/09/2014	1200
Botswana	6/28/2014 - 7/12/2014	1200
Burkina Faso	4/19/2015 - 5/05/2015	1200
Burundi	9/29/2014 - 10/10/2014	1200
Cameroon	1/24/2015 - 2/08/2015	1182
Cote d'Ivorie	8/26/2014 - 9/08/2014	1199
Gabon	9/18/2015 - 10/03/2015	1198
Ghana	5/20/2014 - 7/10/2014	2400
Guinea	3/16/2015 - 4/05/2015	1200
Kenya	11/12/2014 - 12/05/2014	2397
Lesotho	5/05/2014 - 5/31/2014	1200
Liberia	5/06/2014 - 5/22/2014	1199
Madagascar	12/12/2014 - 1/13/2015	1200
Malawi	3/01/2014 - 4/27/2014	2400
Mali	12/01/2014 - 12/14/2014	1200
Mozambique	6/30/2015 - 9/07/2015	2400
Namibia	9/22/2014 - 8/27/2014	1200
Niger	4/01/2015 - 4/18/2015	1200
Nigeria	12/05/2014 - 1/09/2015	2400
Senegal	11/22/2014 - 12/08/2014	1200
Sierra Leone	5/22/2015 - 6/10/2015	1191
South Africa	8/13/2015 - 9/21/2015	2390
Sudan	6/09/2015 - 6/26/2015	1200
Swaziland	4/21/2015 - 5/10/2015	1200
Tanzania	8/26/2014 - 10/19/2014	2386
Togo	10/12/2014 - 10/24/2014	1200
Uganda	5/07/2015 - 5/26/2015	2400
Zambia	10/03/2014 - 10/30/2014	1199
Zimbabwe	11/16/2014 - 11/29/2014	2400

Country	Field Dates	Sample Size
	Round 7	39824
Benin	12/24/2016 - 1/02/2017	1200
Botswana	6/21/2017 - 7/05/2017	1198
Burkina Faso	10/02/2018 - 10/18/2018	1200
Cameroon	5/07/2018 - 5/25/2018	1202
Cote d'Ivoire	12/30/2016 - 1/11/2017	1200
Gabon	11/02/2017 - 11/14/2017	1199
Gambia	7/23/2018 - 8/12/2018	1200
Ghana	9/09/2017 - 9/25/2017	2400
Guinea	5/13/2017 - 5/31/2017	1194
Kenya	9/13/2016 - 10/08/2016	1599
Lesotho	11/25/2017 - 12/11/2017	1200
Liberia	6/19/2018 - 7/16/2018	1200
Madagascar	1/20/2018 - 2/26/2018	1200
Malawi	12/26/2016 - 2/14/2017	1200
Mali	2/08/2017 - 2/24/2017	1200
Mozambique	6/13/2018 - 9/03/2018	2392
Namibia	11/06/2017 - 12/21/2017	1200
Niger	4/13/2018 - 4/30/2018	1200
Nigeria	4/26/2017 - 5/10/2017	1600
Senegal	12/02/2017 - 12/19/2017	1200
Sierra Leone	7/06/2018 - 7/28/2018	1200
South Africa	7/30/2018 - 9/26/2018	1840
Sudan	7/22/2018 - 8/25/2018	1200
Swaziland	3/13/2018 - 3/28/2018	1200
Tanzania	4/30/2017 - 6/17/2017	2400
Togo	11/11/2017 - 11/23/2017	1200
Uganda	12/26/2016 - 1/08/2017	1200
Zambia	4/08/2017 - 4/25/2017	1200
Zimbabwe	1/28/2017 - 2/10/2017	1200

A.3 Variable Descriptions

Name	Description	Source
Incumbent Share	Proportion of valid votes for incumbent executive, party, or party's candidate.	Election commission websites Media reports
Margin	Difference in share of valid votes for incumbent and leading challenger.	Election commission websites Media reports
Turnout	Proportion of registered voters who cast ballots (Includes invalid votes)	Election commission websites Media reports
Months from Harvest	Months from average maximum NDVI date.	USGS, Landsat 5, 7, 8.
Growing Season Length	Days between average maximum and minimum NDVI dates.	USGS, Landsat 5, 7, 8.
GDP PC PPP	Gross Domestic Product per capita, Purchasing Parity Power	World Bank, World Development Indicators
Pct. Employed Ag.	Percentage of the workforce employed in agriculture.	World Bank, World Development Indicators
Pct. GDP from Ag.	Percentage of gross domestic product in agriculture.	World Bank, World Development Indicators
Ramadan	Election occurs during Ramadan.	Wikipedia
Independence Day	Election occurs within two weeks of independence day.	Wikipedia
Christmas	Election occurs within two weeks of Christmas.	Advent calendar
Polity 2	Polity score, level of democracy	Center for Systemic Peace
Econ. Perf.	Respondent says government does fairly or very well at handling the economy.	Afrobarometer
Pov. Perf.	Respondent says government does fairly or very well at improving living standards of the poor.	Afrobarometer
Prices Perf.	Respondent says government does fairly or very well at keeping prices down.	Afrobarometer
Ethnic ID	Respondent identifies as member of ethnic group over nation.	Afrobarometer
Rural	Enumerator recorded location.	Afrobarometer
Age	Respondent's age in years.	Afrobarometer
Discuss Pol.	Respondent discusses politics with friends and family.	Afrobarometer
Employed	Respondent has job that pays cash.	Afrobarometer
Female	Enumerator recorded gender.	Afrobarometer

A.4 Summary Statistics

Table A1: Sub-Saharan Africa

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Incumbent Share	1408	0	0.6	0.3	0.0	0.6	1.0
Margin of Victory	1535	1	0.2	0.5	-1.0	0.3	1.0
Turnout	861	30	0.7	0.2	0.1	0.7	1.0
Months from Max	348	0	5.8	2.9	0.0	5.9	12.2
Polity	17	7	3.5	4.1	-6.0	5.0	9.0
GDP PC PPP	126	0	3323.5	2470.4	475.2	2754.2	15359.7
Pct. Employed Ag.	122	2	53.7	17.3	4.7	51.2	92.2
Pct. GDP Ag.	125	1	25.0	11.7	1.9	25.0	58.9
Ramadan	2	0	0.1	0.2	0.0	0.0	1.0
Independence Day	2	0	0.1	0.3	0.0	0.0	1.0
Christmas	2	0	0.1	0.2	0.0	0.0	1.0
NDVI (Last Harvest)	1184	17	0.5	0.1	0.0	0.5	0.8
Season Length	239	0	186.7	99.9	1.0	190.5	365.0

Table A2: Zambia

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Incumbent Share	300	0	0.5	0.3	0.0	0.5	0.9
Margin of Victory	300	0	0.1	0.5	-1.0	0.2	0.9
Turnout	300	0	0.4	0.1	0.1	0.4	0.6
Months from Max	120	0	8.4	1.5	4.2	8.0	11.2
Season Length	91	0	243.8	42.4	26.0	244.5	350.0
NDVI (Last Harvest)	298	0	0.6	0.1	0.3	0.6	0.7
Urban	2	0	0.3	0.4	0.0	0.0	1.0

Table A3: Afrobarometer

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Econ. Performance	5	6	2.2	1.0	1.0	2.0	4.0
Econ. Performance (Dummy)	3	6	0.4	0.5	0.0	0.0	1.0
Pov. Performance	5	4	2.0	0.9	1.0	2.0	4.0
Pov. Performance (Dummy)	3	4	0.3	0.5	0.0	0.0	1.0
Price Performance	5	4	1.8	0.9	1.0	2.0	4.0
Price Performance (Dummy)	3	4	0.2	0.4	0.0	0.0	1.0
Ethnic ID	3	9	0.5	0.5	0.0	1.0	1.0
Months from Harvest	13	0	5.7	3.2	0.0	5.0	12.0
Rural	2	0	0.6	0.5	0.0	1.0	1.0
Age	88	1	36.8	14.6	18.0	33.0	106.0
Discuss Pol.	4	1	0.9	0.7	0.0	1.0	2.0
Employed	3	0	0.3	0.5	0.0	0.0	1.0
Female	3	0	0.5	0.5	0.0	1.0	1.0
Farmer	3	35	0.3	0.4	0.0	0.0	1.0
Living Conditions	3	2	0.3	0.5	0.0	0.0	1.0

Appendix B: Additional Models

Below I report two sets of additional models. First, I re-estimate my Africa-wide models on a subset of observations with above-average polity scores. Next, I re-estimate my Zambia models swapping province fixed-effects for constituency fixed-effects, and standard errors clustered by province-year for constituency-year.

Table B1: Subnational Elections by Constituency - Polity greater than 3.5

	Incumbent Share		Margin	
	Reduced	Controls	Reduced	Controls
Months from Harvest	0.020**	0.022**	0.043**	0.048**
	(0.008)	(0.008)	(0.015)	(0.016)
Months from Harvest^2	-0.001**	-0.001***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Harvest NDVI		-0.117		-0.376
		(0.189)		(0.344)
GDP PC PPP		0.000+		0.000*
		(0.000)		(0.000)
Pct. Employed Ag.		0.006		0.008
		(0.006)		(0.012)
Pct. GDP from Ag.		-0.017**		-0.016
		(0.006)		(0.012)
Num.Obs.	745	745	738	738
AIC	-792.9	-822.9	128.1	111.5
BIC	-779.1	-790.6	141.9	143.7
RMSE	0.14	0.14	0.26	0.26
Subnat. Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

Standard Errors Clustered by Subnational Unit
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additional Afrobarometer Models

In the main text I report results from a series of OLS regressions using survey data from the Afrobarometer. These four regressions show the relationship between months from harvest and:

- a respondent's evaluation of the incumbent government's performance on the economy (0-3; Strongly disapprove, disapprove, approve, strongly approve),
- a respondent's evaluation of the incumbent government's performance on improving living standards (0-3; Strongly disapprove, disapprove, approve, strongly approve),

Table B2: Zambian Presidential Elections by Constituency

	Incumbent	Margin	Incumbent	Margin
Months from Harvest	0.031*	0.068*	0.026*	0.064*
	(0.013)	(0.026)	(0.010)	(0.023)
Months from Harvest^2	-0.001*	-0.003**	-0.001*	-0.003**
	(0.001)	(0.001)	(0.000)	(0.001)
Lagged DV			0.251	0.100
			(0.210)	(0.230)
Num.Obs.	300	300	300	300
AIC	-66.9	429.7	-76.1	430.7
BIC	-52.1	444.5	-57.6	449.2
RMSE	0.21	0.49	0.21	0.49
Province FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

Standard Errors Clustered by Province-Year

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- a respondent's evaluation of the incumbent government's performance on keeping prices down (0-3; Strongly disapprove, disapprove, approve, strongly approve),
- whether a respondent identifies with their ethnic group more than their nation (0-1).

I repeat these models in several ways. First, I dichotomize ordinal measures by splitting them into agree/disagree, and re-run the same models as linear probability models, logit and probit regressions. Second, I repeat these models on two subsets: farmers, and those who say their present living conditions as very or fairly bad.

Table B3: Seasonality and the Afrobarometer - LPM

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.017***	0.009**	0.006*	0.003
	(0.004)	(0.003)	(0.003)	(0.004)
Months from Harvest^2	-0.001***	0.000*	0.000+	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Harvest NDVI	0.104+	0.149**	0.262***	0.062
	(0.061)	(0.052)	(0.048)	(0.059)
Rural	0.005	-0.004	0.003	0.020**
	(0.007)	(0.006)	(0.006)	(0.006)
Age	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employed	0.003	0.009*	-0.008+	-0.020***
	(0.005)	(0.004)	(0.004)	(0.005)
Female	-0.019***	-0.014***	-0.012***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)
Discuss Pol.	0.000	0.003	0.006*	-0.008**
	(0.003)	(0.002)	(0.002)	(0.003)
Constant	0.019	0.060	0.041	0.966***
	(0.079)	(0.066)	(0.052)	(0.062)
Num.Obs.	108298	110280	109765	105186
R2	0.118	0.110	0.091	0.129
AIC	654449.6	682043.6	683892.2	625692.8
BIC	3232260.9	3323661.3	3301599.7	3238906.0
RMSE	0.46	0.43	0.41	0.47
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included

Standard Errors Clustered by PSU

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4: Seasonality and the Afrobarometer - Logit

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.077***	0.051**	0.053**	0.015
	(0.019)	(0.018)	(0.019)	(0.017)
Months from Harvest^2	-0.004**	-0.003*	-0.003*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Harvest NDVI	0.486+	0.772**	1.769***	0.246
	(0.290)	(0.281)	(0.294)	(0.265)
Rural	0.021	-0.020	0.020	0.090**
	(0.034)	(0.030)	(0.033)	(0.029)
Age	0.001	-0.001	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Employed	0.014	0.049*	-0.047+	-0.093***
	(0.024)	(0.023)	(0.025)	(0.021)
Female	-0.089***	-0.074***	-0.073***	0.103***
	(0.015)	(0.016)	(0.017)	(0.014)
Discuss Pol.	0.001	0.017	0.034*	-0.037**
	(0.013)	(0.013)	(0.014)	(0.013)
Constant	-2.254***	-2.235***	-2.597***	2.601***
	(0.445)	(0.445)	(0.379)	(0.552)
Num.Obs.	108298	110280	109765	105186
R2	0.094	0.093	0.085	0.100
AIC	132864.2	122081.1		130512.1
RMSE	0.46	0.43	0.41	0.47
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included
Standard Errors Clustered by PSU
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B5: Seasonality and the Afrobarometer - Probit

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.047***	0.029**	0.027**	0.009
	(0.011)	(0.010)	(0.010)	(0.011)
Months from Harvest^2	-0.002***	-0.001*	-0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Harvest NDVI	0.308+	0.474**	0.999***	0.155
	(0.175)	(0.166)	(0.167)	(0.163)
Rural	0.012	-0.013	0.010	0.056**
	(0.020)	(0.018)	(0.019)	(0.018)
Age	0.000	0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employed	0.009	0.031*	-0.025+	-0.057***
	(0.015)	(0.013)	(0.015)	(0.013)
Female	-0.055***	-0.045***	-0.044***	0.063***
	(0.009)	(0.009)	(0.010)	(0.008)
Discuss Pol.	0.000	0.009	0.020*	-0.022**
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	-1.376***	-1.338***	-1.510***	1.513***
	(0.258)	(0.249)	(0.211)	(0.291)
Num.Obs.	108298	110280	109765	105186
R2	0.094	0.093	0.085	0.100
AIC	132873.7	122097.4	111066.1	130514.1
RMSE	0.46	0.43	0.41	0.47
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included

Standard Errors Clustered by PSU

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B6: Seasonality and the Afrobarometer - Farmers Subset

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.046***	0.015	0.020	-0.002
	(0.014)	(0.013)	(0.013)	(0.006)
Months from Harvest^2	-0.003***	-0.001	-0.002+	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Harvest NDVI	0.037	0.180	0.325	-0.005
	(0.204)	(0.200)	(0.205)	(0.109)
Rural	-0.010	-0.030	-0.052*	0.018
	(0.028)	(0.028)	(0.026)	(0.014)
Age	0.000	0.000	0.000	-0.001*
	(0.001)	(0.000)	(0.001)	(0.000)
Employed	-0.139***	-0.105***	-0.076***	-0.026+
	(0.024)	(0.023)	(0.022)	(0.014)
Female	-0.032*	-0.007	0.016	0.036***
	(0.015)	(0.015)	(0.014)	(0.008)
Discuss Pol.	0.005	0.020+	0.022+	-0.019**
	(0.012)	(0.011)	(0.011)	(0.006)
Constant	0.638**	0.575**	0.550**	0.901***
	(0.195)	(0.188)	(0.205)	(0.103)
Num.Obs.	17866	18173	18098	17297
R2	0.197	0.139	0.172	0.174
AIC	62489.1	64523.1	66500.9	103855.5
BIC	159328.1	161911.5	160964.8	135575.2
RMSE	0.86	0.85	0.83	0.46
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included

Standard Errors Clustered by PSU

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B7: Seasonality and the Afrobarometer - Bad Living Conditions Subset

	Econ. Performance	Pov. Performance	Price Performance	Ethnic ID
Months from Harvest	0.034***	0.014*	0.012+	0.004
	(0.008)	(0.007)	(0.006)	(0.004)
Months from Harvest^2	-0.002***	-0.001*	-0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Harvest NDVI	0.277*	0.261*	0.394***	0.029
	(0.124)	(0.111)	(0.116)	(0.062)
Rural	0.013	-0.005	0.009	0.018*
	(0.015)	(0.012)	(0.013)	(0.007)
Age	0.000	-0.001*	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employed	-0.005	-0.001	-0.015+	-0.016**
	(0.011)	(0.009)	(0.009)	(0.005)
Female	-0.023***	-0.007	-0.008	0.022***
	(0.007)	(0.006)	(0.006)	(0.004)
Discuss Pol.	-0.016**	-0.005	-0.002	-0.009**
	(0.006)	(0.006)	(0.005)	(0.003)
Constant	1.171***	1.224***	1.235***	0.944***
	(0.160)	(0.125)	(0.116)	(0.062)
Num.Obs.	75242	76511	76299	72501
R2	0.137	0.134	0.117	0.135
AIC	268034.3	286784.0	296527.9	429672.0
BIC	1607426.4	1656474.3	1656437.8	1508556.6
RMSE	0.84	0.81	0.78	0.47
Unit FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Month and Year FEs	Yes	Yes	Yes	Yes

Weights and Survey Design Included

Standard Errors Clustered by PSU

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$