



The effects of cellphone coverage expansion on wealth and political behavior

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Competing Interests

None.

The effects of cellphone coverage expansion on wealth and political behavior

Taking advantage of Ghana's gradual extension of cellphone towers in the early 2000s, we analyze the wealth effects of cellphone coverage expansion in a developing country setting using a difference-in-differences (event study) research design. We proxy local wealth using night-time light density over 1996–2016 and an asset ownership-based index from the 2000 and 2010 censuses. We find that cellphone coverage expansion significantly raised wealth in Ghana. We then explore possible downstream effects of cellphone coverage expansion on electoral outcomes. We find no evidence that betteroff citizens reward incumbents, either in presidential or parliamentary elections. Using Afrobarometer survey data, this null finding appears to be because citizens do not give the government credit for economic improvements that are due to decisions made by private telecommunications companies. Further, increases in cellphone coverage significantly decrease vote-buying, which may be due to voters being harder to buy off when they are better off.

1. Introduction

How does access to cellphones affect citizens' wealth, and what are the downstream implications for voting behavior and citizen attribution of credit for possible improvements in wellbeing? This question has important theoretical and policy implications as access to technology grows disproportionately quickly in the lowest income countries and among the poorest (Kosec and Wantchekon, 2020). If cellphone access expands wealth, it could potentially mitigate income disparities across and within countries, contributing to

achievement of the sustainable development goals (SDGs) and greater political stability. Equally important to attaining these goals, however, is how cellphones affect political behavior. Access to technologies like cellphones may be a private sector achievement, but it could have political consequences that are relevant to assessments of the technology's overall impacts.

A growing body of work explores the socio-economic consequences of cellphone penetration. Cellphones have been shown to increase farmers' incomes by improving productivity (Gupta, Ponticelli, and Tesei, 2023) and reducing information asymmetries between buyers and smallholder sellers (Aker, 2010) as well as price dispersion across markets (Aker and Fafchamps, 2015). Cellphone coverage has also been linked to increased off-farm employment, including casual wage labor, salaried employment, and non-agricultural self-employment (Rajkhowa and Qaim, 2022). Additionally, it can help individuals cope with economic shocks (Jack and Suri, 2014) and reduce infant mortality (Mensah, Tafere, and Abay, 2022).¹ A linked question that this paper considers is to what extent these gains are capitalized into higher wealth levels.

The downstream effects of cellphone coverage on electoral outcomes are more ambiguous. On the one hand, based on theories of economic voting, improved economic conditions should benefit the incumbent government (Duch and Stevenson, 2006), even when the incumbent is not necessarily responsible for the economic gains (Hayes, Imai, and Shelton, 2015). However, cellphone coverage also lowers coordination and information costs, which can increase protests (Christensen and Garfias, 2018), mass mobilization (Manacorda and Tesei, 2020) and, under certain conditions, violent conflict (Pierskalla and Hollenbach, 2013). Especially in countries with weak electoral institutions, improved collective action capacity and lower information costs should generally benefit opposition parties (Arias et al., 2019).

¹ While the net effects are positive, of course, there may be winners and losers.

Further, to the extent that cellphone coverage increases voter wealth, vote-buying may be more costly for politicians. How these countervailing forces play out is an open question, since with few exceptions (Guriev, Melnikov, and Zhuravskaya (2021) and Donati (2022)) there is almost no evidence on whether or how cellphone coverage expansion affects voting behavior in developing country settings.

We address this gap by providing novel evidence on the relationship between cellphone coverage expansion and wealth in Ghana, and further analyzing impacts on citizens' voting behavior and political attitudes. We construct a panel dataset of local level cellphone coverage using high-resolution annual coverage maps and combine it with data on two wealth proxies: nighttime light density during 1996–2016 and household asset ownership (11 indicators, which we combine in a wealth index) from the 2000 and 2010 Ghanaian censuses. We further add voting records for electoral constituencies from six presidential and parliamentary elections (spanning 1996 to 2016). Ghana is a useful case as elections are competitive, resulting in alternation of power between the two main political parties—the New Patriotic Party (NPP) and the National Democratic Congress (NDC)—offering a clean test of the relationship between cellphone coverage and incumbent support.

Since spatial variation in cellphone coverage could be correlated with unobserved determinants of household wealth or electoral outcomes, we use a difference-in-differences (DiD) design. We confirm that our assumption of parallel trends holds when using night-time light density data (for which, unlike the Census data, we have data over more than two time periods), increasing confidence that our estimates can be interpreted as causal.

We find that cellphone coverage expansion predicts significantly higher values of both wealth measures. Given economic improvements, we next analyze whether there is a downstream effect on electoral behavior. We find no evidence—for presidential or

parliamentary elections— that incumbents benefit electorally from cellphone coverage expansion.

We then use Afrobarometer (AB) survey data to analyze possible mechanisms accounting for null voting results. We consider whether voters do not credit the government for economic improvements (perhaps instead crediting the private sector), or give incumbents credit but this credit is insufficient to influence voting (e.g., due to ethnic voting or because the economy is insufficiently salient). We find no evidence that cellphone coverage changed perceptions of government performance in handling the economy. However, it did modestly decrease votebuying—consistent with voters who are better-off being costlier to buy off (Jensen and Justesen, 2014).

We make three contributions to the literature. First, we present evidence on the effects of cellphone coverage on wealth, complementing the literature’s current focus on production, agricultural prices, and employment. This allows us to assess the net welfare impacts of the technology. Further, while existing studies generally focus on the effects of advanced information communications technologies, including 3G and Internet access, our focus is on a more basic form of cellphone technology (2G), largely limited to phone calls and text messages. If wealth gains are seen with this technology, it would suggest that even small improvements in access to cellphone technology are valuable and consequential for poverty reduction.

Second, we contribute to debates about whether economic voting—the idea that citizens reward the government for good economic outcomes and punish it for bad ones—takes place in developing countries. As political parties in many developing countries are not programmatic, and given relatively low levels of political knowledge, it has been argued that voters select candidates with relatively limited attention to performance (Adida et al., 2017). Our study suggests that voters do not exhibit attribution bias (Hayes, Imai, and Shelton, 2015); they do not reward or attribute credit to politicians, who have limited control over

private telecommunications companies, for wealth improvements conferred by cellphone coverage. Cellphones may allow for better information and coordination that counter any gains due to economic voting.

Finally, we contribute to a broad literature on factors influencing voter attribution of credit for economic improvements (Healy, Kosec, and Mo, 2017; Benedictis-Kessner and Warshaw, 2020). Specifically, in the case of wealth-conferring technological improvements in the form of cellphone coverage, we show that there is no discernible incumbency advantage.

2. Context

A lower-middle-income country, Ghana has a diverse and rich resource base. GDP per capita was \$389 (current USD) in 1996, but rose to 1,900 by 2016 (World Bank, 2022), the end of the period we analyze. Income generation is primarily driven by a mix of agricultural activities, fisheries, services, and industry (including mining). Within agriculture, small-scale farming of crops like maize, rice, soybeans, cocoa, cassava, and plantains plays a crucial role in providing income for a significant portion of the population. All areas, but urban areas especially, have economic activity in the growing services sector. Industry continues to be a critically important sector, surpassing agriculture as a greater share of GDP in 2010 (Huq and Tribe, 2018).

Amid this economic growth, cellphone coverage expanded rapidly but unevenly (from zero in 1996 to 80% in 2008, and then near saturation by 2016), as shown in Figure 1 and Table SI-3. This expansion was broadly driven by private sector profit-seeking incentives; we find no evidence of politically motivated incentives (detailed discussion is in Supplementary Information section (SI) G). Since cellphone coverage is consequential only if it increases

cellphone takeup, we confirm in SI Section A that increases in cellphone coverage significantly increase household cellphone ownership (Table SI-1) and usage (Table SI-2).

Politically, Ghana transitioned to multi-party democracy in 1992 after a period of military rule following independence from British colonial rule. Ghana has a highly competitive presidential system with a unicameral parliament. While clientelism is widespread (Brierley and Nathan, 2022) and electoral fraud and electoral violence at times present (Asunka et al., 2019), Ghanaian elections during our study period were relatively free and fair (Brierley and Kramon, 2020).

Two main parties dominate politics in Ghana: the New Patriotic Party (NPP) and the National Democratic Congress (NDC). Both draw support based on ethnic appeals (Michelitch, 2015; Nathan, 2019), often engaging in exclusive forms of mobilization including narratives based on indigeneity (Klaus and Paller, 2017). However, Ghana also has a high number of persuadable swing voters willing to cross party lines (Ichino and Nathan, 2013), especially when targeted with attributable public goods and services (Harding, 2015; Weghorst and Lindberg, 2013). Evaluations and perceptions of parties and candidates are thus important determinants of voting behavior in Ghana (Lindberg and Morrison, 2008; Weghorst and Lindberg, 2013). Our study takes place amid numerous close general elections during 1996–2016, with the winning party switching between the NDC and NPP three times.

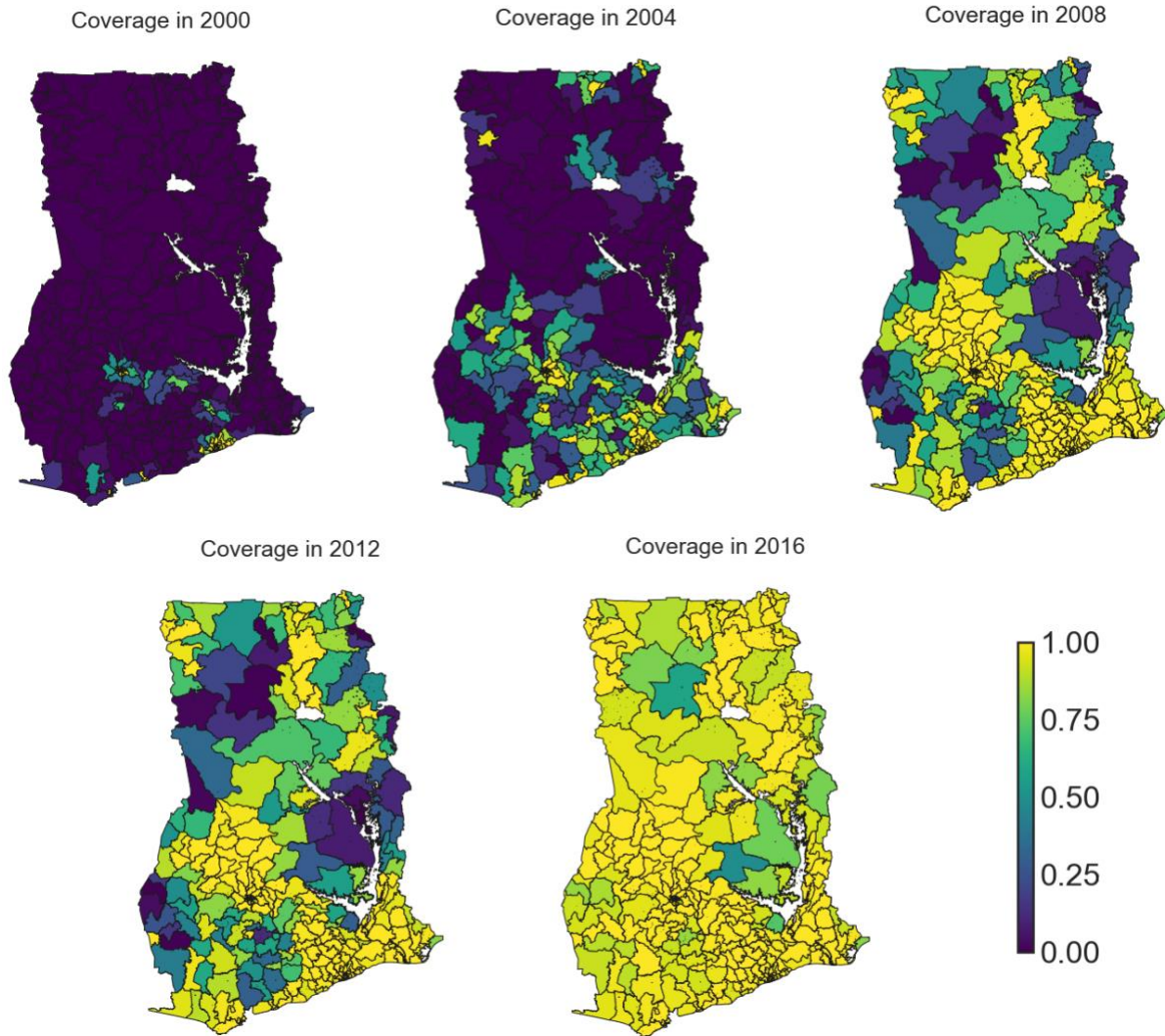


Figure 1. Cellphone coverage expansion between 2000 and 2016 in Ghana. Notes: Each polygon is a parliamentary constituency. Colors represent the share of the population (from 0 to 1) with cellphone coverage in each year, with purple (dark) shade being lower levels and yellow (light) shade being higher levels. Source: GSMA cellphone coverage data.

3. Research design

3.1 Data and variable description

We measure cellphone coverage by spatially merging coverage maps produced by the GSM Association (GSMA) (GSMA, 2019) with the smallest available census geometries (enumeration areas, henceforth EAs), which we then aggregated to the electoral constituency level. Our coverage measure is the share of the population with coverage. Additionally, we construct a binary ‘treatment’ measure, defining a constituency as heavily covered when over 50% of its population has cellphone coverage. We chose this threshold as it has a natural interpretation (individuals are more likely to have than not have cellphone coverage). The number of constituencies with over 50% cellphone coverage increased from zero to 191 out of 193 constituencies over the study period. In Figure SI-1, we display temporal variation in the timing of expansions of cellphone coverage crossing the 50% threshold.

We analyze the relationship between cellphone coverage and wealth using two proxies. First, following Burke et al. (2021), we proxy development with night-time light density, aggregated to the census EA-level using a harmonized dataset from Li et al. (2020). Second, we construct a wealth index that is the average of 11 indicators for ownership of household durable assets from Ghana’s 2000 and 2010 censuses. Table SI-3 presents descriptive statistics for these wealth measures. SI Section B discusses these variables’ construction (other than night-lights, which are described in SI Section D).

We construct a constituency–election year panel dataset for the six elections between 1996 and 2016. We first analyze incumbent vote share in presidential and parliamentary elections, from Ghana’s Electoral Commission. Following conventional practice (e.g., Klašnja and Titiunik, 2017), our focus is on the incumbent’s party rather than individual politicians. We define “incumbent party” as the party in power in the year a constituency crossed the

50% cellphone access threshold (which we use in our binary measure of cellphone coverage). This means that we track the vote share of different parties for different constituencies.² We further analyze voter turnout in each election.

Ghana has created new electoral constituencies over time, primarily by splitting existing constituencies in two. During 1996–2000, Ghana had 200 electoral constituencies; we treat these as the original, “mother” constituencies, and aggregate electoral results of split-off constituencies to this level to study stable constituency units across elections.³

Finally, we use Afrobarometer (AB) survey data from 1999 to 2015 to test the robustness of our wealth findings and explore the impacts of cellphone coverage on government perceptions and reported vote-buying. We aggregated five questions that capture wealth (listed in Table 1) into an index by taking simple averages over individual questions. Our index on perceptions of government performance in handling the economy (plus a broader perceptions of government performance index) are constructed similarly from questions listed in Table 1. More details about AB dataset construction are in SI Section C and summarized in Table SI-4.

3.2 Estimation

We employ a difference-in-differences (DiD) design that leverages within-unit increases in cellphone coverage over time to identify its effects on outcomes of interest. We use the following specifications when analyzing the effect of cellphone coverage expansion:

$$y_{irt} = \tau \text{Coverage}_{irt} + \delta_i + \gamma_t + \varepsilon_{irt} \quad (1)$$

$$y_{irt} = \tau \text{Coverage}_{irt} + \delta_i + \xi_{rt} + \varepsilon_{irt} \quad (2)$$

$$y_{irt} = \tau \text{Coverage}_{irt} + \delta_i + \delta_{it} + \xi_{rt} + \varepsilon_{irt} \quad (3)$$

² For example, since constituency Afigya Sekyere East had a large increase in coverage between 2000 and 2004 when the NPP was in power, the NPP is the party for which we analyze swings in its vote share across years.

³ We drop the eight constituencies (4% of all) created out of portions of two or more earlier constituencies.

where i indexes EAs (for election outcomes, constituencies), r indexes regions, and t indexes elections. y_{irt} is a wealth outcome (night-time light density or asset wealth) or electoral outcome (incumbent vote share or turnout) and $\text{Coverage}_{irt} \in [0,1]$ is the population share with cellphone coverage in EA i in year t , described in sub-section 3.1.

Eqn 1 is a two-way fixed effects regression that partials out the effects of possibly timeinvariant EA-level confounders δ_i and uniform year shocks γ_t and yields consistent estimates if the parallel trends assumption holds, conditional on these fixed effects. However, this specification may yield biased estimates in the presence of time-varying EA-specific confounders.

Eqn 2 addresses this by incorporating region \times year fixed effects, which account for region-level wealth shocks. Eqn 3, further adds EA-level linear time trends, which identifies the treatment effect of coverage from departures from EA-level trends in wealth or electoral outcomes.

In panel data settings with staggered treatment adoption and heterogeneous treatment effects, two-way fixed effects often produce biased estimates as they implicitly average over multiple DiD comparisons, including some where already treated units serve as controls for newly treated units (Goodman-Bacon, 2021). Several estimators that correct this bias have been proposed; we use the fixed effects counterfactual estimator (FEct), an imputation method that restricts to untreated periods in the estimation of the unit and time fixed effects (Borusyak, Jaravel, and Spiess, 2023; Liu, Wang, and Xu, 2024). It first estimates a fixed effect counterfactual model (represented by Eqn 1) that fits parameters using only untreated units and imputes counterfactual outcomes for treated units (the outcomes as if the treated units were not treated). The average treatment effect on the treated (ATT) is calculated by averaging across treatment cohorts. We report event study plots for the FEct for both wealth and electoral outcomes.

When analyzing AB data which comprise repeated cross-sections of individuals and not panel data, we estimate the following equation:

$$y_{irt} = \alpha \text{Coverage}_{irt} + \zeta Z_{it} + \theta_t + \varepsilon_{irt} \quad (4)$$

where i indexes respondents, t indexes years, and θ_t are year fixed effects. Z_i comprises individual level demographic and geo-spatial controls summarized in Table SI-4. We estimate specifications with and without EA-level pre-treatment covariates derived from the 2000 Ghanaian census, as described above.

Table 1. Afrobarometer variable construction

Category	Variable name	Question	Original response	Re-coding
Individual-level controls	Age	How old are you?	Numeric value of age	
	Male indicator	Respondent's gender	1 = Male; 0 = Female	
	Secondary or higher education	What is your highest level of education?	0 = no formal schooling; 1 = informal schooling only 2 = some primary schooling; 3 = primary school completed 4 = intermediate school or some secondary school / high school 5 = secondary school / high school complete 6 = post-secondary qualifications, other than university 7 = some university; 8 = university completed; 9 = post_graduate	
	Christian	What is your religion, if any?		1 = Christian; 0 = not Christian
	Muslim	What is your religion, if any?		1 = Muslim; 0 = not Muslim
	Distance to border (km)	(Latitude, Longitude)		
	Distance to Accra (km)	(Latitude, Longitude)		
	Distance to constituency centroid (km)	(Latitude, Longitude)		
	Distance to main road (km)	(Latitude, Longitude)		
	Distance to any road (km)	(Latitude, Longitude)		

Wealth index	Enough food	Over the past year, how often, if ever, have you or anyone in your family gone without enough food to eat?	0 = never 1 = just once or twice 2 = several times 3 = many times 4 = always	0 = always 1 = many times 2 = several times 3 = just once or twice 4 = never
	Enough water	Over the past year, how often, if ever, have you or anyone in your family gone without enough clean water for home use?		
	Enough medicine	Over the past year, how often, if ever, have you or anyone in your family gone without medicines or medical treatment?		
	Enough cooking food	Over the past year, how often, if ever, have you or anyone in your family gone without enough fuel to cook your food?		
	Enough cash income	Over the past year, how often, if ever, have you or anyone in your family gone without a cash income?		
Economy-related government performance measures	Price stabilized	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Keeping prices stable?	1 = very badly 2 = fairly badly 3 = fairly well 4 = very well	
	Inequality reduced	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Narrowing gaps between rich and poor?		

	Economy improved	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say? Managing the economy		
	More jobs created	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say? Creating jobs		
	Better food provision	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Ensuring everyone has enough to eat?		
	Better water condition	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Providing water and sanitation services?		
Other government performance measures	Crimes reduced	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Reducing crime?	1 = very badly 2 = fairly badly 3 = fairly well 4 = very well	
	Better health services	How well or badly would you say the current government is handling this matter, or haven't		

		you heard enough to say: Improving basic health services?		
	Better education	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Addressing educational needs?		
	Less corruption	How well or badly would you say the current government is handling this matter, or haven't you heard enough to say: Fighting corruption in government?		
	HIV / AIDS issue improved	How well or badly would you say the current government is handling the following matters, or haven't you heard enough about them to say: Combating HIV/AIDS?		
Other outcomes	Vote buying	And during the last national election, how often, if ever did a candidate or someone from a political party offer you something, like food or a gift or money, in return for your vote?	0 = never 1 = once or twice 2 = a few times 3 = often	

4. Wealth Results

We first analyze the wealth effects of cellphone coverage expansion, considering our two main proxies for local wealth: night-time light density over 1996–2016 and an index based on asset ownership indicators from the 2000 and 2010 Ghanaian censuses.

4.1 Night-time light density

Table 2 reports results from our night-time light density wealth measure. These data are available at the (granular) EA level; we take the EA-level mean (across pixels) and normalize by EA population. When estimating Eqns 1–3, cellphone coverage expansion predicts greater nighttime density. In our models with full controls, obtaining heavy (i.e., > 50% of the population) cellphone coverage predicts a 0.114 S.D. (narrowly short of significance at the 10% level) increase in night-time light density (column 3), and a 1 S.D. increase in our continuous measure of cellphone coverage predicts a 0.057 S.D. increase (significant at the 10% level) in night-time light density (column 6). As shown in Table SI-5, results are substantially unchanged and typically more statistically significant when using the EA-level mean (across pixels) (Panel A), as well as when using the mean or the sum but not normalizing by population (Panels B–C).

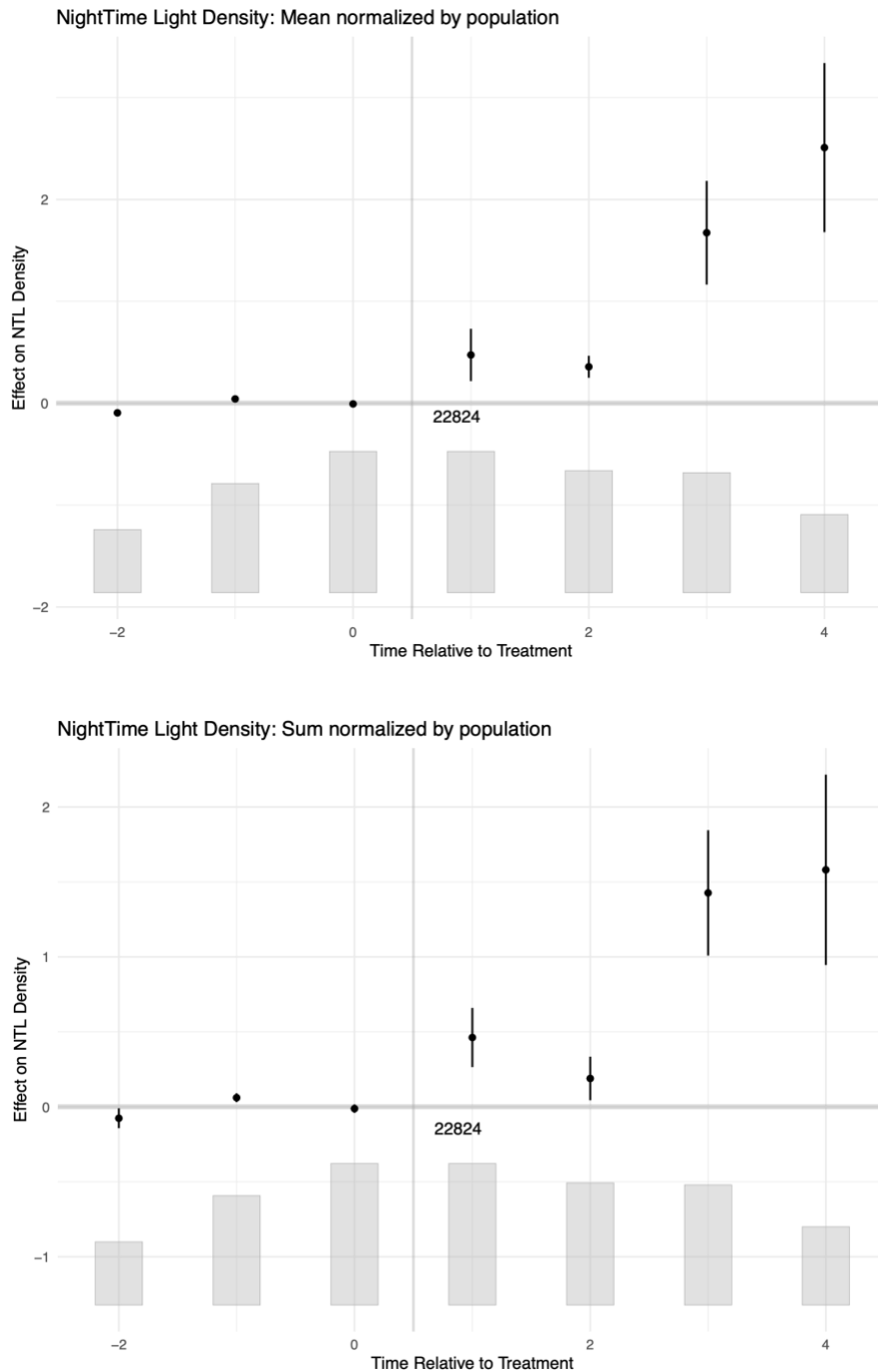
Table 2. Night-time light density wealth measure results

	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone coverage	0.583*** (0.067)	0.319*** (0.070)	0.114 (0.071)	0.317*** (0.030)	0.187*** (0.030)	0.057* (0.033)
Observations	140 952 0.93	140 952 0.94	140 952 0.97	140 952 0.93	140 952 0.94	140 952 0.97

Notes: This table presents estimates for analysis using night-time light density data at the EA level aggregated as the mean normalized by population. The independent variable is dichotomous in models (1)-(3) (which correspond to Eqns 1-3, respectively), and continuous in models (4)-(6) (which correspond to Eqns 1-3, respectively). The dichotomous measure of cellphone coverage takes on a value of 1 if at least 50% of the constituency population has coverage. The continuous measure captures the share of a constituency population with coverage. All models include EA fixed effects. “EA vary slope” indicates the presence of EA-level time trends. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Source: GSMA and Li et al. (2020).

One potential concern is time heterogeneity bias produced by the staggered rollout of cellphone coverage across the country (Goodman-Bacon, 2021) and potential violation of the parallel trends assumption. As discussed in Section 3.2, this concern is addressed in two ways. First, Eqn 3 partially accounts for this by incorporating region-year intercepts that restrict comparisons to within the same region and election (column 3 and 6 of Table 2). Second, we use the FEct estimator, which is robust to heterogeneous effects (Liu, Wang, and Xu, 2024). The event study plots in Figure 2 displays the dynamic effects of expanding cellphone coverage from below to above 50%. The x-axis displays the period relative to the date a constituency became “treated” using our discrete measure of cellphone coverage (i.e., passed the threshold of $> 50\%$ of the population having cellphone coverage). A value of 1 refers to one period after a constituency passes said threshold, and a value of -1 refers to one period beforehand. Using this alternative specification, we find that the effect is around 0.5 for the first period after a constituency obtains cellphone coverage. This is the case whether we use the mean or sum of night-time light density normalized by population. Encouragingly, we see no effects in pre-treatment periods.

Figure 2. Event study plots: Night-time light wealth measures



Notes: Event study plots use the FEct, where treatment status takes on a value of 1 if cellphone coverage exceeded 50%. 'Treatment' is an absorbing state; in our dataset, no constituency or EA changes cellphone coverage from above 50% to below. The x-axis is time relative to treatment. The y-axis is the effect of cellphone coverage expansion on night-time light density, aggregated as the mean normalized by population. Source: GSMA and Li et al. (2020).

4.2 Census data

Night-time light density has a few drawbacks as a proxy for economic activity. First, night-time light density may capture both government investment in electricity and household wealth. Secondly, many EAs have no night-lights recorded, especially in earlier years. This may mask some economic growth, especially in locations without electricity. This motivates us to additionally analyze a household wealth index constructed from 2000 and 2010 census data, which we aggregate to the constituency level. As Table 3 shows, we again find that greater cellphone coverage predicts greater wealth. The results hold whether our unit of analysis is the EA (columns 1--2) or the constituency (columns 3--4) (the latter is the geographical unit when we analyze electoral outcomes).

The EA-level regression using first differences and our full set of controls (column 2) suggests that a 1 S.D. increase in cellphone coverage leads to a 0.071 S.D. increase in the wealth index value over this period, while the analogous constituency-level regression yields a 0.33 S.D. increase in wealth. In all models, the coefficients on cellphone coverage are significant at the 1% level. Results are further robust to instead using a wealth index constructed from AB data (Table 4, columns 1--2). For analysis of all component variables of the AB wealth index, see Table SI-6.

Table 3. Census wealth index results

	(1)	(2)	(3)	(4)
Δ Cellphone coverage	0.065*** (0.008)	0.071*** (0.008)	0.310*** (0.088)	0.329*** (0.090)
Observations	22421	22421	22421	193
R^2	0.034	0.044	0.044	0.254
Administrative level	EA	EA	EA	Constituency
Controls	No	Yes	Yes	Yes

Notes: All models are first-difference specifications, where changes in the wealth index are regressed on changes in the continuous cellphone coverage measure (both standardized to have mean 0 and standard deviation 1). All models include region fixed effects. Model 2 and model 4 include EA level and Constituency level controls, respectively, for the shares of the population from ethnic groups that traditionally support the NPP and NDC. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Source: Cellphone coverage data are from GSMA; wealth data are from the 2000 and 2010 censuses.

Table 4. Wealth, government performance in handling the economy, and vote buying results using Afrobarometer data

	Wealth index		Gov. perf index (economy)		Vote buying	
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone coverage	0.076*** (0.015)	0.071*** (0.015)	0.003 (0.0015)	0.004 (0.016)	-0.058** (0.025)	-0.051** (0.025)
Observations	7663	7663	7015	7015	3055	3055
R^2	0.49	0.50	0.18	0.18	0.05	0.05
EA controls	No	Yes	No	Yes	No	Yes

Notes: "Wealth index" and "gov. perf. index (economy)" are constructed from AB all rounds. "Vote-buying" is only asked in rounds 3 and 5. All models include individual-level controls. Robust standard errors are shown in parentheses: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Source: GSMA and Afrobarometer.

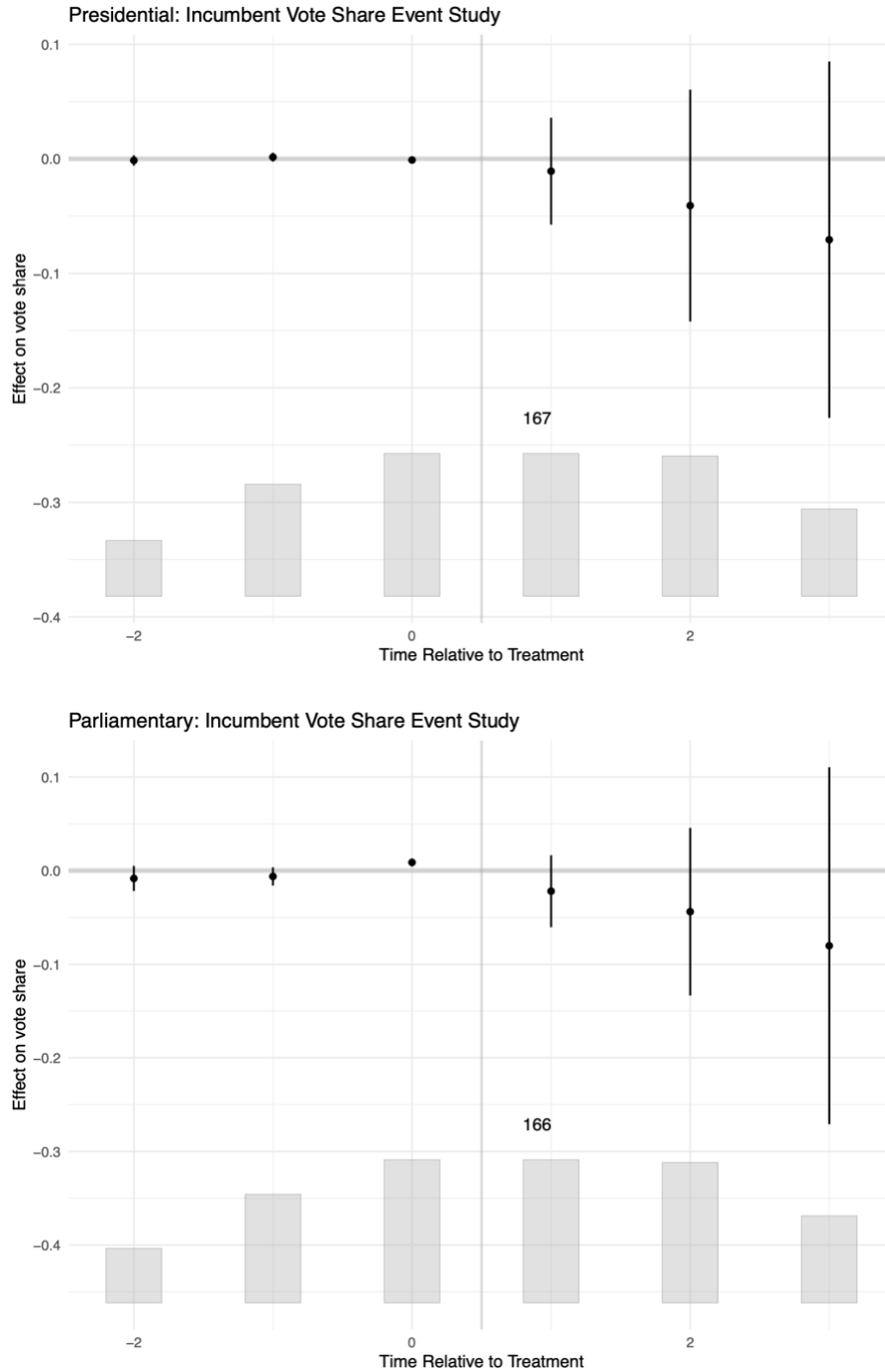
Alternative causal mechanism: additional infrastructure investment

The above results suggest that cellphone coverage directly improves citizens' wealth—signaling its potential political importance, given theories of economic voting. It is possible, however, that other local infrastructure changes may coincide with expansion of cellphone towers, leading to biased estimates of the effects of cellular technology. We analyze this possibility in Tables SI-11 and SI-12, which consider the impacts of cellphone coverage expansion on road density and village electrification projects, respectively. For both, we see inconsistent and generally null results; the data and analyses are described in more detail in SI Section H. While imperfect, these analyses increase our confidence that this alternative mechanism is not biasing estimates of the effects of cellphone coverage expansion.

5. Electoral results

A key question is whether these findings have any political implications. Existing literature suggests that the effects could go either way; on the one hand, as we showed above, cellphone coverage expanded economic opportunities in Ghana. This could spur economic voting, which benefits the incumbent party (LewisBeck and Stegmaier, 2008). On the other hand, cellphones may improve voter coordination (Guriev, Melnikov, and Zhuravskaya, 2021), facilitate voter mobilization by political parties or brokers, and increase pressure (from one's social network) to vote (Enrcíquez et al., 2023). Additionally, we might expect decreases in vote-buying with cellphone coverage expansion because it is costlier to buy the votes of richer individuals (Jensen and Justesen, 2014). These alternative channels do not a-priori advantage incumbent relative to opposition parties. It is therefore unclear, ex-ante, whether and how the dramatic expansion of cellular technologies in the past two decades affects aggregate electoral outcomes.

Figure 3. Event study plots: Electoral outcomes



Notes: See notes from Table 2. Source: cellphone coverage data are from GSMA; presidential and parliamentary electoral outcome data are from the Electoral Commission of Ghana.

5.1 Effects on voting behavior

Using the FEct estimator, we find no evidence that cellphone coverage has a downstream effect on the vote share of the incumbent party for either presidential or parliamentary elections, as shown in Figure 3. Further, this does not appear to be due to changes in voter turnout that might be offsetting greater or lesser support among existing voters (Table SI-8). We also do not find consistent evidence that cellphone coverage expansions matter more in more competitive constituencies, defined by the incumbent's margin of victory in 1996 (SI Section F, Table SI-9).

5.2 Robustness and model assumptions

Parallel trends are challenging to evaluate because: (1) cellphone coverage treatment is continuous and (2) our sample includes only one pre-treatment period (1996). Nevertheless, we can analyze whether coverage was strategically expanded to constituencies favoring the incumbent by regressing past electoral outcomes (lagged by four years) on contemporaneous cellphone coverage. As SI Section G shows, we find little evidence of such targeting (Table SI-10).

5.3 Effects on perceived government performance in handling the economy

A natural question is whether citizens do not reward the incumbent for wealth improvements because they do not attribute these to good government performance, or because improved perceptions of performance are not sufficiently large or salient to alter voting patterns. We find little evidence that cellphone coverage affected perceptions of government performance on economy-related issues (Table 4, columns 3–4).⁴ Further, considering other dimensions of government performance (generally related to service

⁴ These are listed in Table 1, alongside the full list of government performance questions.

delivery and perceived corruption), as well as an index using all government performance questions, we similarly find generally null results (Table SI-7).

5.4 Effects on vote-buying

Voting may also be affected by how wealth changes the prevalence of vote buying. Voters may be more costly to buy off when they are better-off. To test this possibility, we consider how often individuals reported a candidate or someone from a political party offering them food, gifts, or money in return for their vote.⁵ In our preferred (full controls) specification, a 1 S.D. increase in cellphone coverage predicts a 0.05 S.D. decrease in vote-buying (Table 4, columns 5–6).

6. Conclusion

We explore the effect of cellphone coverage expansion on wealth in Ghana using a difference-in-differences design complemented by fixed effects counterfactual estimation. We find that cellphone coverage expansion significantly raised wealth. We further test whether citizens reward the incumbent for making them relatively better off and do not find evidence that this is the case; neither for presidential nor parliamentary elections is the incumbent vote share significantly affected (and nor does voter turnout change). Further, cellphone coverage does not improve perceptions that the government is handling the economy well. However, increases in cellphone coverage appear to reduce vote-buying, which may be due to voters being harder to buy off when they are better-off.

To the extent that government deserves credit for enabling private sector investment, perhaps it is disconcerting for electoral accountability that we find no evidence of economic voting. However, if incumbents exert little influence on where private telecommunications

⁵ This question was only asked in AB rounds 3 (2005) and 5 (2012).

companies invest in new cellphone towers, this lack of credit attribution for wealth improvements is appropriate and encouraging as it points to voter sophistication.

Future work should further explore the implications of cellphone coverage for a broader set of voting patterns—including how these vary across different types of voters. It should also test the generalizability of our findings to additional wealth-conferring communication technologies beyond 2G cellphone coverage as well as to other developing countries. As Ghana has a relatively large reservoir of persuadable voters, and its elections are both competitive and relatively fair, we do not expect to find a more positive electoral response to 2G cellphone coverage expansions in most other developing country settings.

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Supplementary information

A. Validation of cellphone coverage measure

An essential assumption for all mechanisms linking cellphone coverage and political outcomes is that cellphone coverage leads to increased ownership and usage of cellphones. To verify the effect of cellphone coverage on cellphone ownership we use Demographic and Health Surveys (DHS), which include the question, “Does your household have a mobile telephone?” across multiple survey rounds. We include all four rounds in which DHS included this question and collected latitude and longitude coordinates. These surveys were conducted in 2008, 2014, 2016, and 2017. We measure cellphone coverage for DHS respondents with the GSMA data using the procedure described in SI Section B.

Models follow the same cross-sectional specifications we use to analyse Afrobarometer data, shown in Eqn 4. We include pretreatment household-level covariates: age and gender of the household head. As with the regressions using Afrobarometer data, we also include pretreatment covariates derived from the 2000 Ghanaian census: EA-level wealth score and the share of population likely to support the NPP and likely to support the NDC. Results shown in Table SI-1 reveal that cellphone coverage increases household cellphone ownership by over 17 percentage points when moving from zero to full cellphone coverage. We evaluate the increase in cellphone use due to cellphone coverage using Afrobarometer rounds 4 and 5, surveyed in 2009 and 2012. These are the only Afrobarometer surveys that include questions that allow us to measure changes in cellphone use over time during the timeframe of the GSMA coverage data. In the round 4 survey, Afrobarometer asked, “How often do you use: A mobile phone?” and coded responses of never, less than once a month, a few times a month, a few times a week, or every day. In round 5, Afrobarometer split the question on cellphone use into three questions: “How often do you normally use a mobile phone to: Make or receive a call?”, “How often do you normally use a mobile phone to: Send

or receive a text message or SMS?”, and “How often do you normally use a mobile phone to: Send or receive money or pay a bill?” In round 5, the responses were coded never, less than one time per day, one or two times per day, three or four times per, or five or more times per day.

From these questions we construct two variables, measuring both the extensive and intensive margins of cellphone use. The first is a variable indicating the respondent used a cellphone at all, for any purpose. The second is a variable indicating the respondent used a cellphone at least daily, coded as 1 if the respondent answered that they used a cellphone for any of these purposes once or more a day and 0 if the respondent reported using a cellphone less than once a day or never. Specifications follow Eqn 4 and include pretreatment household-level covariates and other pretreatment covariates derived from 2000 Ghanaian census as described in SI section B. Results shown in Table SI-2 show that cellphone coverage both increases the likelihood individuals ever use a cellphone and the likelihood they use a cellphone daily.

Table SI-1. Cellphone ownership results, using DHS data

	Standardized variables		Unstandardized variables	
	(1)	(2)	(3)	(4)
Cellphone coverage	0.038*** (0.002)	0.038*** (0.002)	0.178*** (0.010)	0.176*** (0.010)
Observations	52379	52379	52379	52379
R^2	0.206	0.208	0.206	0.208
Const. controls	No	Yes	No	Yes

Notes: This table presents coefficient estimates for household cellphone ownership using DHS data. All models are cross-sectional specifications as shown in Eqn 4. All models include pretreatment household-level controls, the age and gender of the household head. In models (1)-(2) variables for cellphone coverage, wealth, and the percentage of the population that are members of ethnic groups that tend to vote for the NPP and NDC have been standardized to a mean of 0 and a standard deviation of 1. In models (3)-(4) these variables have not been standardized. Const. stands for the constituency. All models include household-level control variables. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Source: cellphone coverage data are provided by the GSM Association; cellphone ownership data are from DHS.

Table SI-2. Cellphone use results, using Afrobarometer (AB) data

	Ever use cellphone		Use cellphone daily	
	(1)	(2)	(3)	(4)
Cellphone coverage	0.026*** (0.007)	0.025*** (0.007)	0.015** (0.008)	0.014* (0.008)
Observations	3320	3320	3320	3320
R^2	0.210	0.213	0.213	0.255
Const. controls	No	Yes	No	Yes

Notes: This table presents coefficient estimates for daily cellphone use using data from Afrobarometer rounds 4 and 5. All models are cross-sectional specifications as shown in Eqn 4. Models (1)-(2) have an outcome indicating whether the respondent ever reports using a cellphone. The outcome of models (3)-(4) is whether the respondent reports using a cellphone daily. All models include pretreatment individual-level controls. Const. stands for the constituency. All models include individual-level control variables. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Source: cellphone coverage data are provided by the GSM Association; cellphone usage data are from Afrobarometer.

B. Main analysis data construction

The unit of analysis in our primary political outcomes analysis is the electoral constituency. We construct a panel dataset of constituency-level electoral data, cellphone coverage, and census data (e.g., demographics and measures of wealth) for the six elections between 1996 and 2016 as described below.

Electoral Data (key outcome variables) The dependent variables are electoral outcomes from the 1996, 2000, 2004, 2008, 2012, and 2016 presidential and parliamentary elections provided by the Electoral Commission of Ghana at the constituency level. The number of constituencies was increased twice during the period of our study. There were 200 constituencies during the 1996 and 2000 elections. This was increased to 230 constituencies for the 2004 and 2008 elections. This was increased again to 275 constituencies for the 2012 and 2016 elections. These new constituencies were primarily the result of splitting existing constituencies in two. To construct a panel with stable constituency units across elections, we aggregate the electoral results of constituencies that were split into the earliest constituency units, the 200 1996/2000 constituencies. We also join split constituencies in the 2016 constituency shapefile to create the 1996/2000 shapefile that we use to calculate cellphone coverage. Several cases of new districts that were not simple splits of existing districts or ambiguous constituency names in the electoral data required dropping several constituencies. The resulting dataset has between 188 and 196 constituencies for each election. We merge the constituency-level electoral data with EA-level cellphone coverage and census data, first spatially merging the EA-level geometries with a constituency shapefile that gives us unique constituency identifiers.

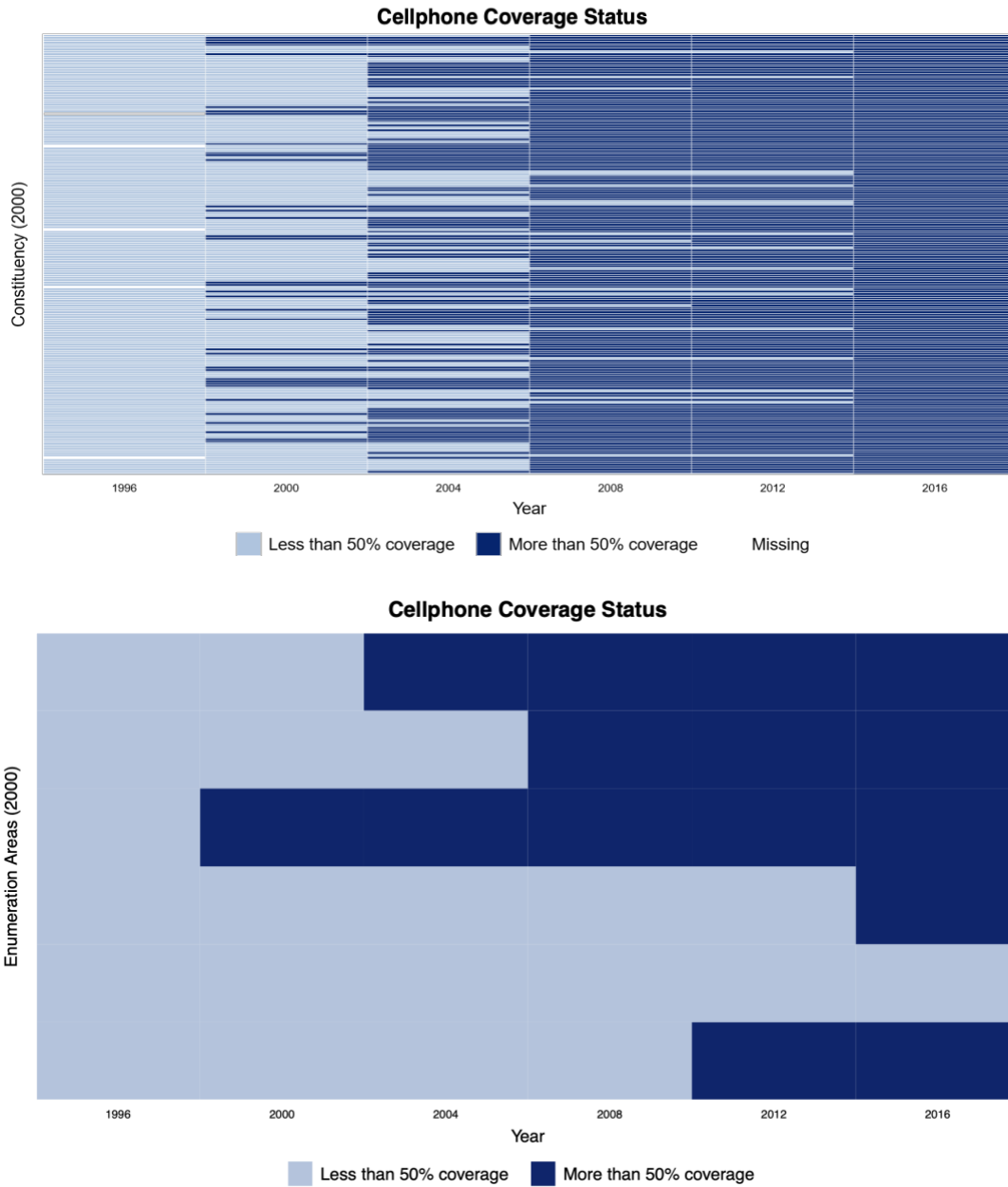
GSMA Data (key independent variable) Our key input variable was constructed using coverage maps purchased from the GSM Association (GSMA), a cellphone network provider industry group, which collects and reports global cellphone coverage data in partnership with Collins Bartholomew, a digital mapping provider. This dataset has been used in past

research, including Buys et al. (2009), Pierskalla and Hollenbach (2013), Christensen and Garfias (2018), and Manacorda and Tesei (2020). The Collins Bartholomew data comes from submissions made by cellphone operators in each country to construct roaming coverage and is reported in the form of (approximately) yearly global coverage shapefiles outlining the extent of 2G, 3G, and 4G coverage (GSMA, 2019). We convert these polygons into rasters,⁶ for easier subsequent processing. We then aggregate the EA-level cellphone coverage measure to the constituency level by taking a population-weighted average of EA-level coverage measures. Figure 1 shows cellphone coverage expansion in Ghana between 2000 and 2016 at the constituency level. In Figure SI-1, we display temporal variation in the timing of expansions of cellphone coverage crossing the threshold of 50% or more of the population covered.

Ghanaian Census We obtained Enumeration-Area (EA) level data for the 2000 and 2010 census and EA-level shapefiles from the Ghanaian Statistical Service (GSS). We merge the two censuses with their corresponding geometries to construct an EA-level panel dataset. We then spatially merge the EA-level census dataset with yearly cellphone coverage rasters to construct coverage measures for each year between 2000 and 2008. We compute zonal statistics, which average the value of a raster in each polygon. In this case, since the raster values are binary, this gives us the share of each EA that has cellphone coverage in each year. Computations were performed using rasterstats, a Python module for summarizing geospatial raster datasets.

⁶ Since the coverage polygons are binary, the rasterization simply converts these coverage extents into matrices of binary coverage indicators at the cell (0.05 decimal degrees, or 5 km at the equator) level. Rasterisation was performed using <https://corteva.github.io/geocube/stable/index.html>.

Figure SI-1. Dichotomized cellphone coverage status by year



Notes: Plots display whether cellphone coverage for each constituency (top panel) or each EA (bottom panel) is above 50% or below, indicated by the color of the cell. The x-axis is the year. The y-axis is the administrative level. Each cell in the top panel represents one constituency in one year. The bottom panel presents EAs with the same initiation year of achieving over 50% cellphone coverage binned together. Source: GSMA.

Wealth measures

Household wealth is a key outcome in this study's causal chain. The 2000 and 2010 EA-level census datasets contain the following eleven variables that proxy wealth: share of households with a roof made of materials better than earth, mud, bamboo, or leaf; share of households with walls made of materials better than earth or mud; share of households with a floor made of materials better than earth or mud; share of households with electricity; share of households using sewerage system; share of household with piped-water; share of households with collected rubbish; share of households with toilets; share of households with improved water source; share of the population that is not forced to work for profit; and literacy rate. We standardized these proxy variables across the 2000 and 2010 censuses so that they are at the same scale and in the same direction (larger value indicates greater wealth). These variables are positively correlated with each other and have high consistency based on Cronbach's alpha (larger than 0.8). We constructed a wealth score by taking a simple average across these wealthrelated variables. It was further standardized to have mean 0 and standard deviation 1.

Table SI-3, Descriptive statistics, main analysis

Panel A: Dependent variables						
Wealth measures	Mean	Median	St. Dev.	Min	Max	N
Constituency Level						
Wealth Index (2000)	39.324	38.681	15.607	11.995	75.473	216
Wealth Index (2010)	45.753	45.153	13.598	16.024	74.587	216
Enumeration Area Level						
Wealth Index (2000)	46.251	46.586	20.352	1.998	94.709	22421
Wealth Index (2010)	50.753	52.578	17.596	0.417	98.213	22421
Nightlight Density Mean (1996)	2.923	0	9.545	0	63	23964
Nightlight Density Mean (2000)	3.005	0	9.545	0	62	23964
Nightlight Density Mean (2004)	3.288	0	9.725	0	59	23964
Nightlight Density Mean (2008)	3.263	0	9.798	0	60	23964
Nightlight Density Mean (2012)	4.116	0	11.442	0	63	23964
Nightlight Density Mean (2016)	6.934	5.551	12.027	0	62	23964
Nightlight Density Sum (1996)	3.497	0	10.503	0	63	23964
Nightlight Density Sum (2000)	3.626	0	10.398	0	62	23964
Nightlight Density Sum (2004)	3.888	0	10.392	0	59	23964
Nightlight Density Sum (2008)	3.829	0	10.393	0	60	23964
Nightlight Density Sum (2012)	4.907	0	12.278	0	63	23964
Nightlight Density Sum (2016)	7.713	6	12.697	0	62	23964
Independent Variable						
Cellphone Coverage (2000)	0.191	0	0.347	0	1	196
Cellphone Coverage (2004)	0.516	0.552	0.377	0	1	196
Cellphone Coverage (2008)	0.809	0.952	0.264	0	1	196

Cellphone Coverage (2012)	0.826	0.954	0.254	0	1	196
Cellphone Coverage (2016)	0.969	0.988	0.0481	0.731	1	195

Panel B: Other variables

Constituency Level						
% Ethnic-NPP (2000)	0.385	0.332	0.308	0.011	0.911	216
% Ethnic-NDC (2000)	0.507	0.502	0.294	0.058	0.966	216
Population (2000)	85433	78250	44819	1987	301783	196
Population Density (2000)	1210	103	3664	1.48	26068	196
Enumeration Area Level						
% Ethnic-NPP (2000)	0.398	0.308	0.349	0	1	22421
% Ethnic-NDC (2000)	0.504	0.519	0.344	0	1	22421

Notes: This table presents descriptive statistics for variables used in our main analysis. For both presidential and parliamentary elections, the vote share is the vote share of the incumbent party.

C. Afrobarometer Data Construction

We studied mechanisms and performed robustness tests by using publicly available, nationally representative Afrobarometer (AB) survey data. We scrutinized survey questions in each round thoroughly and selected pertinent questions that mainly target the following five key outcome categories: wealth (as a robustness check on the census wealth index described above), faith in economy, evaluation of government performance, and reported vote buying. For each of these outcome categories, we constructed an index utilizing all of the component variables capturing that outcome category.

Starting with the geo-labeled Afrobarometer (AB) data, we located most of the respondents in Enumeration Areas and the rest, 2000 constituencies. We further assigned each respondents EA-level covariates values. We used all data available from round 1 (1999) to round 6 (2015). We excluded the last two rounds because the year in which they were

conducted post-dated the last election in our study. When common questions included in different rounds have different response categories, we re-coded responses (e.g., by collapsing categories where applicable) so that they are consistently and comparably coded across rounds. We also re-coded responses such that larger values always represent better outcomes (e.g., more wealth, greater faith in the economy or more positive perceptions of government performance). Note that not all variables are included in every AB round. We utilized as many rounds as possible for each outcome. Indexes are by construction missing for a round if any of its component variables is missing for that round. Details on each component variable in each category, along with their original question wording and response re-coding scheme, are detailed in Table 1.

Individual-level controls include both demographic and geospatial variables. Age is a continuous variable. Education is re-coded as an indicator for the respondent having completed secondary education or higher. Religion is re-coded into three dummies: Christian, Muslim, or other. Gender is an indicator for male respondents. Moreover, using respondents' coordinates, we calculated the distance to Ghana's border, Accra, the closest constituency centroid, the shortest distance to major roads, and shortest distance to any road for each respondent.

EA-level controls are generated from 2000 census data, including wealth index, and share of population that would most likely support NPP or NDC based on ethnicity. Note that for less than 5% respondents, we could not locate their EA because available geo-coded administration boundary datasets lack information for some EAs. For those respondents, we impute values of control variables using constituency-level values.

Wealth index is constructed as the simple average of five questions that ask respondents how often in the last year they have gone without food, water, medicine, cooking fuel, or cash income. These variables take on a value from 0 (always gone without food, etc.) to 4 (never gone without food, etc.).

Government performance index is comprised of a series of questions about respondents' perceptions of how well the government is dealing with the following issues: the economy, health services, education, water access, food supply, job opportunities, price stability, inequality, crime, corruption, and HIV-AIDS. Responses range from 1 (very badly) to 4 (very well).

Vote buying is a question asked only in rounds 3 and 5 about whether the respondent got paid or offered anything in return for their vote.

Descriptive statistics: All Afrobarometer variables that appear in our empirical analysis are summarized in Table SI-4.

Table SI-4. Descriptive statistics, individual-level Afrobarometer (AB) analysis

Treatment Variable	Mean	Median	St. Dev.	Min	Max	N	Round
Cellphone Coverage	0.741	1	0.421	0	1	9061	Round 1-6
Dependent Variables							
Welfare							
Wealth Index	2.149	2.133	0.626	0	6	9061	Round 1-6
Enough food	3.411	4	1.029	0	4	9041	Round 1-6
Enough water	3.283	4	1.197	0	4	9048	Round 1-6
Enough medicine	3.292	4	1.137	0	4	9019	Round 1-6
Enough cooking fuel	3.57	4	0.912	0	4	7750	Round 2-6
Enough cash income	2.581	3	1.378	0	4	7725	Round 2-6
Government Performance							
Government performance index	2.323	2.375	0.765	1	4	8974	Round 1-6
Economy improved	2.334	2	1.025	1	4	7521	Round 2-6
More jobs created	2.079	2	0.972	1	4	8757	Round 1-6
Price stabilized	1.962	2	0.976	1	4	8862	Round 1-6
Inequality reduced	1.94	2	0.939	1	4	8575	Round 1-6
Crime reduced	2.558	3	1.049	1	4	8808	Round 1-6

Better Health Services	2.57	3	1.008	1	4	8861
Better education	2.526	3	1.013	1	4	8865 Round 1-6
Better water condition	2.352	2	1.002	1	4	7592 Round 2-6
Better food provision	2.237	2	0.979	1	4	7460 Round 2-6
Less corruption	2.238	2	1.055	1	4	8482 Round 1-6
HIV/AIDS issue improved	3.11	3	0.906	1	4	5110 Round 2-5
Political Knowledge						
MP	0.582	1	0.493	0	1	2141 Round 3,4
Minister of Finance	0.216	0	0.412	0	1	1083 Round 4
Local gov. councilor	0.307	0	0.462	0	1	1058 Round 3
Deputy president	0.704	1	0.457	0	1	1058 Round 3
Party with the most seats	0.733	1	0.442	0	1	1058 Round 3
Term limits knowledge	0.693	1	0.462	0	1	1058 Round 3
Const. law knowledge	0.144	0	0.351	0	1	1058 Round 3
Vote buying	0.164	0	0.587	0	3	3055 Round 3,5
Individual-level controls						
Age	40	35	43	18	99	9061
Male indicator	0.497	0	0.5	0	1	9061
Secondary or Higher education	0.485	0	0.5	0	1	9061
Christian	0.636	1	0.481	0	1	9061
Muslim	0.123	0	0.328	0	1	9061
Distance to border (km)	57.815	36.059	56.161	0.008	185.754	9061
Distance to Accra (km)	202.794	184.723	162.961	1.303	648.536	9061
Distance to constituency centroid (km)	7.647	6.468	6.457	0.089	43.919	9061
Distance to main road (km)	18.941	6.584	27.046	0.002	148.703	9061
Distance to any road (km)	1.116	0.448	1.712	0	18.048	9061

Notes: This table presents descriptive statistics for variables used in our AB analysis.

D. Night-Time Light Density

Following Burke et al. (2021), we proxy local wealth with Night-time Light Density from a recently published harmonized dataset (Li et al., 2020). This dataset re-calibrated and integrated two sources of night-time light satellite data: the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) (1992-2013) and the Visible Infrared Imaging Radiometer Suite (VIIRS) (2012). Night-time light density is recorded as a number ranging from 0 to 63, with 30 arc-seconds spatial resolution. We aggregated night-time light density in pixels up to the EA-level using zonal statistics. Our main analysis from Table 2 aggregates the data to the EA-level using the mean across pixels and normalizes this amount by EA population. Table SI-5 shows that these findings are not sensitive to using the sum rather than the mean to aggregate, or to whether or not we normalize by EA population.

Table SI-5. Night-time light density wealth measure results, robustness to alternative methods of construction

Panel A: NightTime Light Density Sum Normalized by Population						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.837*** (0.067)	0.525*** (0.067)	0.340*** (0.083)	0.419*** (0.032)	0.260*** (0.031)	0.158*** (0.037)
Observations	140 952	140 952	140952	140952	140952	140952
R^2	0.91	0.91	0.96	0.91	0.91	0.96
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
EA vary slope	No	No	Yes	No	No	Yes

Panel B: NightTime Light Density Mean						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.175*** (0.022)	0.105*** (0.021)	-0.021 (0.021)	0.101*** (0.011)	0.066*** (0.010)	-0.010 (0.011)
Observations	140 952	140 952	140952	140 952	140 952	140 952
R^2	0.95	0.95	0.98	0.95	0.95	0.98
Panel C: NightTime Light Density Sum						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.292*** (0.024)	0.207*** (0.025)	0.087*** (0.025)	0.146*** (0.012)	0.103*** (0.012)	0.038*** (0.012)
Observations	140 952	140 952	140 952	140 952	140 952	140 952
R^2	0.95	0.98	0.98	0.95	0.95	0.98
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
EA vary slope	No	No	Yes	No	No	Yes

Notes: This table presents coefficient estimates for analysis using night-time light density data. The independent variable is the dichotomous cellphone coverage measure in models (1)-(3), whereas continuous in models (4)-(6). Model (1) and model (4) follow model specification expressed in Eqn 1. Model (2) and model (5) use Eqn 2, models (3) and (6) correspond to Eqn 3. All models have EA-level fixed effects. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Source: cellphone coverage data are provided by the GSM Association; Night-Time Light Density data are constructed by Li et al. (Li et al. (2020)) using satellite imagery from the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS).

E. Analysis of Mechanisms: Afrobarometer Analysis

While in the main text (Table 4) we report only the effect of cellphone coverage on indices of interest (specifically, our wealth index and a government performance index utilizing only economy-related performance issues), below we report in addition the results for each of those indices' constituent variables, in addition to government performance variables not related to the economy.

Wealth Regression results are displayed in Table SI-6. Results for individual variables that composited the wealth index are also presented in the table. The effect of cellphone coverage on wealth is robust and comes from a number of different variables for which we identify statistically significant results: having enough food, enough medicine, and enough cash income.

Table SI-6. Afrobarometer wealth results

	Wealth index		Enough food		Enough water		Enough medicine		Enough cooking fuel		Enough cash income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cellphone coverage	0.076*** (0.015)	0.071*** (0.015)	0.041*** (0.015)	0.043*** (0.015)	0.010 (0.015)	0.010 (0.015)	0.073*** (0.015)	0.070*** (0.015)	0.020 (0.018)	0.017 (0.018)	0.026 (0.016)	0.021 (0.016)
Observations	7663	7663	9041	9041	9048	9048	9019	9019	7750	7750	7725	7725
R ²	0.49	0.50	0.04*	0.04	0.04	0.05	0.08	0.08	0.02	0.02	0.10	0.11
Const. controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table presents coefficient estimates for wealth measures in Afrobarometer round 1 (1999) to round 6 (2015). Models (1), (2), (9)-(12) are missing round 1. The dependent variables in each model are listed in the top row. Detailed question wording, variables re-coding, and all individual-level controls that are included in all models are listed and explained in Table 1. Const. stands for the constituency. All models include individual-level fixed effects and do not have Region × Year fixed effects. Robust standard errors are shown in parentheses: p < 0.01; p < 0.05; p < 0.1.

Government performance: We did not find evidence of cellphone coverage improving people's perceptions of government performance. These generally null effects are reported in Table SI-7.

Table SI-7. Afrobarometer government performance results

	Government performance index		Economy improved		More jobs created		Price Stabilized		Inequality reduced		Crimes reduced	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cellphone coverage	-0.018 (0.016)	-0.016 (0.016)	0.013 (0.015)	0.015 (0.015)	-0.021 (0.014)	-0.022 (0.014)	-0.013 (0.014)	-0.013 (0.014)	-0.007 (0.015)	-0.006 (0.015)	0.022 (0.014)	0.021 (0.014)
Observations	4521	4521	7521	7521	8757	8757	8862	8862	8575	8575	8808	8808
R ²	0.09	0.09	0.17	0.17	0.10	0.10	0.11	0.11	0.05	0.05	0.07	0.07
	Better Health Services		Better education		Better water condition		Better food provision		Less corruption		HIV/AIDS issue improved	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cellphone coverage	-0.015 (0.013)	-0.014 (0.013)	- 0.024*	- 0.023*	0.000 (0.016)	0.000 (0.016)	-0.014 (0.016)	-0.012 (0.016)	- 0.041***	- 0.039***	-0.018 (0.017)	(12) -0.016
Observations	8861	8861	8865	8865	7592	7592	7460	7460	8482	8482	5110	(0.017)
R ²	0.15	0.15	0.15	0.15	0.09	0.09	0.13	0.13	0.15	0.16	0.04	5110
Const. controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table presents coefficient estimates for respondents' perception of government performance from Afrobarometer. The dependent variable in each model is listed in the top row. Detailed question wording, variables re-coding, and all individual-level controls that are included in all models are listed and explained in Table 1. Const. stands for the constituency. All models include individual-level fixed effects and do not have Region × Year fixed effects. Robust standard errors are shown in parentheses: p < 0.01; p < 0.05; p < 0.1.

Voter turnout: We complement our analysis of the incumbent vote share in presidential and parliamentary by analyzing voter turnout in the same elections. Results presented in Table SI-8 confirm no statistically significant impacts on voter turnout for either presidential (Panel A) or parliamentary (Panel B) elections. Thus, our null results for the incumbent vote share do not appear to be due to changes in how many people turn out to vote that might be offsetting greater or lesser support among existing voters. Of course, it is possible that the identities of voters may be changing, with new voters offsetting those who stop voting—but overall levels of support for the incumbent remain the same.

Table SI 8. Voter turnout results

Panel A: Presidential election						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.015 (0.030)	0.025 (0.032)	0.023 (0.034)	0.011 (0.019)	0.019 (0.022)	0.022 (0.025)
Observations	1116	1116	1116	1116	1116	1116
R^2	0.31	0.33	0.57	0.31	0.33	0.57
Panel B: Parliamentary election						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	-0.007 (0.017)	0.023 (0.021)	0.019 (0.021)	0.012 (0.014)	0.024 (0.020)	0.021 (0.019)
Observations	1101	1101	1101	1101	1101	1101
R^2	0.26	0.29	0.48	0.26	0.29	0.48
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
Const. vary slope	No	No	Yes	No	No	Yes

Notes: This table presents estimates for turnout in presidential (Panel A) and parliamentary (Panel B) elections. The independent variable is the dichotomous cellphone coverage measure in models (1)-(3) (which correspond to Eqns 1-3, respectively), and continuous in models (4)-(6) (which correspond to Eqns 1-3, respectively). All models include constituency-level 2000 census controls (a wealth index, and two variables capturing the shares of the population from ethnic groups likely to support the NPP and the NDC, and a dummy variable indicating whether the incumbent power in charge of cellphone coverage expanding to above 50% is in power in each year) interacted with year indicators, as well as constituency fixed effects. Const. stands for the constituency. Const. vary slope indicates the presence of constituency-level time trends. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Electoral Commission of Ghana and GSMA.

F. Heterogeneous effects: competitiveness

While we find that, on average, there is a null effect of cellphone coverage expansion on electoral behavior, this result might hide important heterogeneity. Even though Ghanaian elections are competitive nationally, locally, many elections are not necessarily competitive. When elections are locally lopsided, it might not be prudent for voters to use performance information and remove support from the stronghold party. Following that logic, it is possible that in competitive areas, where one's vote is more likely to be perceived as pivotal, voters will be more likely to use performance signals and exhibit economic voting.

To test this possibility, we conducted a new empirical analysis, interacting our measure of cellphone coverage expansion with the incumbent's margin of victory (MoV) in the 1996 (first period) elections, since MoV is commonly used as a proxy measure of competitiveness. As we report in Table SI-9, we find broadly null results on the interaction term between cellphone coverage and competitiveness.

Table SI 9. Vote share results by margin of victory (continuous competitiveness measure)

Panel A: Presidential election						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.017** (0.008)	0.016** (0.008)	0.012 (0.009)	-0.006 (0.006)	-0.007 (0.006)	-0.003 (0.006)
Cellphone Coverage × Competitiveness	-0.011* (0.006)	-0.025*** (0.008)	-0.017** (0.007)	-0.002 (0.003)	-0.010** (0.005)	-0.005 (0.004)
Observations	1116	1116	1116	1116	1116	1116
R ²	0.95	0.96	0.98	0.95	0.96	0.98
Panel B: Parliamentary election						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	-0.004 (0.014)	0.000 (0.014)	-0.017 (0.016)	0.010 (0.008)	0.014 (0.009)	0.004 (0.010)
Cellphone Coverage × Competitiveness	0.029 (0.022)	0.026 (0.027)	-0.007 (0.034)	0.019 (0.012)	0.018 (0.015)	-0.014 (0.020)
Observations	1097	1097	1097	1097	1097	1097
R ²	0.76	0.78	0.85	0.76	0.78	0.85
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
Const. vary slope	No	No	Yes	No	No	Yes

Notes: This table presents a heterogeneous treatment effect analysis of incumbent vote share in presidential (Panel A) and parliamentary (Panel B) elections. The independent variable is the dichotomous cellphone coverage measure in models (1)-(3) (which correspond to Eqns 1-3, respectively), and continuous in models (4)-(6) (which correspond to Eqns 1-3, respectively). Competitiveness is measured as the margin of victory in the 1996 presidential/parliamentary elections and standardized to have mean 0 and standard deviation being 1. The higher value of competitiveness indicates more competitive elections (smaller margin of victory). All models include constituency-level 2000 census controls interacted with year indicators, as well as constituency fixed effects. Const. stands for the constituency. Const. vary slope indicates the presence of constituency-level time trends. Robust standard errors are shown in parentheses: p < 0.01; p < 0.05; p < 0.1. Data source: Electoral Commission of Ghana and GSMA.

G. Reverse causality

In Table SI-10, we examine whether cellphone coverage expansions were strategically rolled out to regions favoring the incumbent, which would invalidate the causal conclusions we draw from the panel regressions in the main paper. To test this, we regress the present cellphone coverage expansion on past incumbent vote share (considering a four year lag). Large positive coefficients for incumbent vote share in these regressions would suggest that coverage expansions were targeted at constituencies that already favored the incumbent and invalidate our conclusions. They would suggest that political considerations—as opposed to merely private sector profit maximization—motivated these expansions of cellphone coverage. As we see in Table SI-10, we observe no robust impacts of the vote share of the incumbent in presidential elections or the vote share of the incumbent in parliamentary elections on future cellphone coverage expansions. In our preferred specification which estimates Eqn 3 (columns 3 and 6), we see that this form of targeting was statistically indistinguishable from 0, which gives us confidence in the validity of our study's design.

Table SI 10. Regressions of present coverage expansions on past electoral outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Vote Share Presidential	-0.005 (0.050)	0.004 (0.053)	0.117 (0.091)			
Vote Share Parliamentary				0.051 (0.033)	0.052* (0.028)	0.049 (0.038)
Observations	940	940	940	911	911	911
R^2	0.91	0.92	0.94	0.85	0.88	0.90
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
Const. vary slope	No	No	Yes	No	No	Yes

Notes: This table analyzes whether or not we find evidence of reverse causality analysis. In all models, the dependent variable is the current year's continuous cellphone coverage measure standardized to be with mean 0 and standard deviation 1. Models (1)-(3) use presidential election data and models (4)-(6) analyze parliamentary election data. Model (1) and model (4) correspond to the model specification expressed in equation 1. Model (2) and model (5) use equation 2, and model (3) and (6) correspond to equation 3. The key independent variable of interest is the incumbent's vote share in year $t - 4$. All models include constituency-level 2000 census controls (a wealth index, and two variables capturing the shares of the population from ethnic groups likely to support the NPP and the NDC, and a dummy variable indicating whether the incumbent power in charge of cellphone coverage expanding to above 50% is in power in each year) interacted with year indicators, as well as constituency fixed effects. Const. stands for the constituency. Const. vary slope indicates the presence of constituency-level time trends. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Data source: Electoral commission of Ghana.

H. Roads and Electricity

First, we follow Müller-Crepon, Hunziker, and Cederman (2021) and construct a road quality measure by transforming the corpus of Michelin road maps into a digital road atlas akin to time-varying Google Maps. Our measure of road density takes the total kilometers (km) of all types of roads within a constituency, weights them by the road type/quality, and then divides the weighted sum by the constituency's surface area (square km). Armed with this measure (which we have for 1996, 2003, 2007, and 2014), we then regress road quality in time $t + 1$ on our geo-coded measure of constituency mobile coverage at time t . As we

report in Table SI-11, we do not find evidence that road investment has followed cellphone coverage expansion.

Second, we analyze electrification data from Briggs (2021). This paper uses information from the Electricity Company of Ghana (ECG) to measure the number of villages in Ghanaian districts the government connected to the national grid, over time. Importantly, the ECG data come with some limitations noted on page 105391: the dataset coverage is limited to the south, data-years do not overlap perfectly with election years, and the matching of villages from the ECG's lists to the Census listing is imperfect. Nonetheless, because electrification is closely related to our measure of nighttime light density, and because the data cover over 75% of Ghana's residents, analyzing these data is important. Specifically, we test whether electrification in time $t + 1$ follows cellphone coverage expansion in time t . Note that for this analysis, we first had to map electrification data from the district to the constituency level, as described in online appendix G. Again, as with the road data, we find no evidence of infrastructure clustering using the electrification data (see Table SI-12).

Table SI 11. Road Density

Panel A: Road density (full panel)						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Observations	968	968	968	968	968	968
R^2	0.97	0.97	0.98	0.97	0.97	0.98

Panel B: Road density (three years panel)						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	0.001 (0.001)	0.001 (0.001)	0.019 (0.021)	0.012 (0.014)	0.024 (0.020)	0.021 (0.019)
Observations	587	587	587	587	587	587
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
Const. vary slope	No	No	Yes	No	No	Yes

Notes: This table presents regression estimates from regressing road quality on cellphone coverage expansion. The independent variable is the dichotomous cellphone coverage measure in models (1)-(3) (which correspond to Eqns 1-3, respectively), and continuous in models (4)-(6) (which correspond to Eqns 1-3, respectively). Road quality is calculated as the density of the weighted sum of road length weighted by road types. Panel A uses data from four years: 1996, 2003, 2007, and 2014. Panel B only uses data from three years, omitting year 1996 as a robustness check (this is motivated by the fact that road and cellphone data in more recent years are in better quality. And cellphone coverage before 1996 has been 0 everywhere, omitting year 1996 could reduce noises). All models include constituency-level 2000 census controls interacted with year indicators, as well as constituency fixed effects. Const. stands for the constituency. Const. vary slope indicates the presence of constituency-level time trends. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Data source: African road network data (Müller-Crepon, Hunziker, and Cederman, 2021).

Table SI 12. Electrification

Panel A: Electricity (most precise)						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	-0.249 (0.684)	0.256 (0.699)	-0.709 (0.818)	0.081 (0.457)	0.399 (0.466)	-0.480 (0.563)
Observations	372	372	372	372	372	372
R^2	0.55	0.64	0.85	0.55	0.65	0.85
Panel B: Electricity (less precise)						
	Discretized			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Cellphone Coverage	-0.704 (1.255)	0.265 (1.325)	-2.123 (1.602)	0.027 (0.823)	0.676 (0.834)	-1.372 (1.207)
Observations	372	372	372	372	372	372
R^2	0.59	0.68	0.87	0.59	0.68	0.87
Year FE	Yes	No	No	Yes	No	No
Region x Year FE	No	Yes	Yes	No	Yes	Yes
Const. vary slope	No	No	Yes	No	No	Yes

Notes: This table presents results for analyzing whether electrification follows cellphone coverage expansion. The independent variable is the dichotomous cellphone coverage measure in models (1)-(3) (which correspond to Eqns 1-3, respectively), and continuous in models (4)-(6) (which correspond to Eqns 1-3, respectively). Electrification is manually coded by Briggs (Briggs (2021)), allowing different levels of potential coding errors. Panel A uses the most precise electrification measure suggested by the author while Panel B uses a less precise version as a robustness check. All models include constituency-level 2000 census controls interacted with year indicators, as well as constituency fixed effects. Const. stands for the constituency. Const. vary slope indicates the presence of constituency-level time trends. Robust standard errors are shown in parentheses: $p < 0.01$; $p < 0.05$; $p < 0.1$. Data source: Electricity Company of Ghana.

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