Internet Access and Political Engagement: Evidence from South Africa*

Georgiy Syunyaev† Alexis Y. Jang‡ Anna M. Wilke§
Benjamin Laughlin¶ Kholekile Malindi‖

August 21, 2026

[PRELIMINARY DRAFT; DO NOT CITE]

Abstract

Internet access is expanding in low- and middle-income contexts, yet its political effects remain unclear and may depend on how people connect. We study a pre-registered field experiment in a low-income South African township, where the high cost of mobile data constrains use. Around the 2024 national election, we randomly provided households with 8–12 months of uncapped home internet and cross-randomized exposure to an online get-out-the-vote campaign. Combining household surveys, verified turnout, and behavioral traces, we find that home connections increase in-person local political engagement—attendance at ward/community meetings and complaints to ward/municipal officials—while leaving voter turnout and online political participation unchanged. We detect no systematic shifts in political knowledge, views, or broad news consumption patterns. Evidence is consistent with a behavioral channel in which home connectivity raises time spent at home and incidental exposure to local governance, with suggestively stronger effects among men. The results show that expanding home internet, distinct from mobile data, can strengthen place-based participation without mobilizing online activism or turnout, underscoring that the mode of access conditions the political consequences of going online.

*With sincere thanks to Project Isizwe, especially Tim Genders and Siobhan Thatcher, for being excellent implementing partners. Thank you also to Genesis Analytics and DataQuest, especially Sizani Mthembu, Elzeth Zastrau, Jan Schenk, and all the hardworking enumerators. We are also grateful to Craig Rivett for contributing to the conception of this project. We thank the Weidenbaum Center at Washington University in St. Louis for funding. We are grateful to John Marshall for excellent comments on early versions of this project. This project received IRB approval from the New York University Abu Dhabi (Protocol HRPP-2023-90), Washington University in St. Louis (Protocol REC 3/17/05/23), Stellenbosch University (Project number: 26970), and BRANY IRB (Protocol 24-267-734). Pre-analysis plans are available at https://osf.io/4z7t2/overview and https://osf.io/cv5hk/overview.

†Assistant Professor at the Department of Political Science, Vanderbilt University; Email: g.syunyaev@vanderbilt.edu

‡Ph.D. candidate at the Department of Political Science, Washington University in St. Louis; Email: alexis.jang@wustl.edu

§Assistant Professor at the Department of Politics, New York University; Email: amw703@nyu.edu

¶Assistant Professor of Political Science at New York University Abu Dhabi; Email: benjamin.laughlin@nyu.edu

‖Lecturer in the Department of Economics, Stellenbosch University; Email: kholekile@sun.ac.za

1 Introduction

The rapid expansion of digital media has transformed political life across much of the world, yet its consequences for democratic participation remain contested. Early research in advanced democracies suggested that broadband internet access could weaken traditional forms of political engagement, as citizens substituted news consumption with online entertainment and disengaged from electoral politics (Prior 2005; Falck, Gold and Heblich 2014; Campante, Durante and Sobbrio 2018; Gavazza, Nardotto and Valletti 2019). In these settings, internet access often appeared to provide an exit from politics rather than a catalyst for civic participation. Subsequent work, however, documented how digital connectivity can also lower barriers to participation, facilitate coordination, and enable new political actors to mobilize supporters (Campante, Durante and Sobbrio 2018; Zhuravskaya, Petrova and Enikolopov 2020). Taken together, this literature highlights that the political effects of the internet are neither uniform nor inevitable.

A growing body of research has turned to developing countries, where the trajectory of internet adoption differs sharply from that of the Global North. In much of Africa, Asia, and Latin America, the internet arrived first through mobile phones rather than fixed broadband connections at home. Studies of mobile internet expansion in these contexts show that connectivity can increase political participation, protest activity, and electoral competition, largely by lowering information and coordination costs (Manacorda and Tesei 2020; Enikolopov, Makarin and Petrova 2020; Donati 2023). Other work shows that internet access can affect political behavior through additional channels, including shifts in political identity and economic conditions, with implications for participation and accountability (Choi, Laughlin and Schultz 2025; Ge et al. 2025). This literature has been essential for understanding the political consequences of the first stage of internet adoption—the transition from being offline to being online.

Yet this transition does not capture the full range of changes currently underway across the Global South. While some countries continue to face limited or uneven access to the internet, overall connectivity has expanded dramatically over the past three decades, and gaps in mobile internet access are steadily narrowing. In many settings, digital platforms are now embedded in everyday life. Users in these contexts are already online and increasingly internet-literate, but their engagement is often shaped by strict data caps that constrain sustained or data-intensive use. A new wave of infrastructure investment is now beginning to alter this picture, as uncapped fixed broadband—particularly fiber-to-the-home (FTTH)—is rolled out at scale. Across Africa, fiber broadband subscriptions reached 4.7 million in 2022, a 43% increase in a single year, and are projected to grow by 245% between 2022 and 2028. South Africa leads the continent in fiber development, ranking highest among African countries in the Fiber Development Index (Reed, Mbongue and Njue 2023). These developments point to a second stage of internet expansion in parts of the Global South, in which the key change lies not in whether people are connected, but in how connectivity is experienced and integrated into daily life, from constrained mobile data to uncapped home access.

Despite the scale and commitment of public and private investments, existing research offers limited evidence on how changes in access conditions affect political engagement. Fixed home internet differs from mobile internet access in two important respects. First, it relaxes data constraints, allowing for more sustained and data-intensive forms of use. Second, it ties internet access to a fixed physical location, increasing the amount of time individuals spend at home. These changes suggest that home internet can reshape not only what individuals consume online, but also where they spend time and how online activity interacts with local social and political environments. These mechanisms operate differently from those emphasized in earlier studies of internet adoption in both developed and developing countries, which focus on the initial transition from offline to online access.

This paper exploits a unique moment in South Africa's digital development to examine the political effects of expanding home internet access in a population that is already widely connected through mobile phones. South Africa exemplifies a reversed adoption sequence relative to most high-income democracies. By the early 2020s, mobile internet penetration was widespread, yet the costs of mobile data remained high in low-income communities. These costs may constrain both the intensity and the kind of online activity residents can sustain, limiting use beyond social media, messaging, and light browsing, and making data-intensive content (e.g., long-form video, streaming, and sustained news consumption) comparatively costly. At the same time, home broadband access remained limited in low-income communities because of cost and infrastructure constraints. Only recently has uncapped home internet begun to diffuse into townships, offering households a qualitatively different mode of connectivity. This transition provides a rare opportunity, and likely a closing one as saturation approaches, to study the marginal political effects of home internet access in a partially connected society.

We analyze a pre-registered field experiment conducted in a low-income township in KwaZulu-Natal province around the 2024 South African national election. In collaboration with a local internet provider, we randomly assigned 200 out of 400 households in one low-income township to receive 8–12 months of free, uncapped home Wi-Fi access. The intervention represents a substantial change in the mode of connectivity for households that previously relied primarily on prepaid mobile data. We combine household surveys, verified turnout measures, and behavioral indicators to estimate the causal effects of home internet access on political participation, political knowledge, attitudes, and media consumption.

Our results challenge prevailing expectations about how expanded connectivity affects democratic engagement. Access to uncapped home internet did not increase voter turnout, online political participation, political knowledge, or broad patterns of news consumption. Instead, we find that home internet access increased in-person political engagement at the local level, including attendance at community and ward meetings and direct complaints to ward councilors and municipal officials. These effects are substantively meaningful and concentrated in interactions with local government rather than with political parties or national politics.

Evidence from mechanism analyses suggests that these effects are not driven by changes in political beliefs or increased consumption of online political information. Rather, the results are consistent with a behavioral channel in which home internet access alters how individuals allocate their time. Because the provided connection could only be used at home, treated respondents spent more time in their households. This increased presence appears to have heightened awareness of service-delivery failures—such as disruptions to electricity, water, and sanitation—that provide concrete reasons to contact local officials, thereby strengthening place-based political participation. The effects are suggestively larger among men, who in this context are more likely than women to spend time away from home absent the intervention.

This paper makes three contributions to the literature on digital media and political participation. First, it provides causal evidence on the political effects of expanding home broadband access in a setting where mobile internet is already widespread. In contrast to studies of mobile internet expansion that document increased turnout and protest activity (Manacorda and Tesei 2020; Donati 2023), we show that introducing home internet does not increase voter turnout or online political participation. Second, the results demonstrate that internet access can reshape political behavior through behavioral and spatial channels rather than through information acquisition. Home internet access increases in-person engagement with local government without shifting political knowledge, attitudes, or overall news consumption. Third, the study highlights the importance of the mode of connectivity for democratic engagement. Whereas mobile internet facilitates communication and online mobilization (Zhuravskaya, Petrova and Enikolopov 2020), the introduction of home internet in a mobile-saturated context appears to strengthen place-based participation by altering how individuals allocate time and attention within their communities.

Taken together, these findings suggest that the political consequences of internet expansion depend not only on whether citizens are connected, but on how and where that connection is experienced. As many societies move from widespread mobile connectivity toward broader access to home internet, understanding these marginal effects is essential for assessing how digital infrastructure shapes democratic participation.

2 Internet Access and Political Participation

How does access to the internet affect political participation? Existing theories identify several mechanisms through which internet access may increase or decrease political engagement. Most existing explanations emphasize how internet access alters information exposure and media choice. Internet access alters the cost and content of political information, as well as how individuals allocate time and interact socially. As a result, its net effect on participation is theoretically ambiguous and likely context-dependent (Zhuravskaya, Petrova and Enikolopov 2020).

A prominent argument in the literature is that internet access increases political participation by lowering the costs of acquiring political information (Campante, Durante and Sobbrio 2018; Manacorda and Tesei 2020). Online access reduces barriers to news consumption and increases incidental exposure to political content during otherwise non-political activities (Prior 2005). Greater exposure may raise political knowledge and interest, which in turn can encourage participation (Boulianne 2009, 2015). In this view, digital connectivity expands the informational foundations of participation by increasing both the quantity of political content and the probability of encountering it.

Beyond increasing the quantity of information, internet access may also affect its composition and geographic scope. A growing literature argues that digital media amplify national political narratives at the expense of locally embedded information, contributing to the nationalization of political behavior (Hopkins 2018; Martin and McCrain 2019). Compared to traditional media, online platforms often provide easier access to national political news, elite discourse, and national-level controversies. This shift may increase the salience of national politics relative to local issues, potentially strengthening engagement with national elections and parties, while attenuating attention to local governance (Hopkins 2018). The claim that the internet contributes to a "nationalization" of politics–by amplifying elite narratives and national frames–has been made frequently, particularly in the U.S. context (Hopkins 2018). At the same time, online environments expose individuals to misinformation, emotionally charged content, and algorithmically amplified outrage, while political elites—particularly those relying on populist or anti-establishment appeals—have increasingly used digital platforms for mobilization (Tucker et al. 2018; Zhuravskaya, Petrova and Enikolopov 2020). These dynamics suggest that internet access may increase certain forms of participation while simultaneously intensifying ideological and affective polarization.

Competing theories emphasize that internet access may instead reduce political participation by crowding out political information with entertainment-oriented content (Prior 2005). Online environments offer abundant non-political content, including social media, streaming services, and gaming. Expanded media increase access to entertainment, enabling substitution away from political content and reducing engagement even as overall media consumption rises (Falck, Gold and Heblich 2014; Olken 2009). This entertainment substitution mechanism operates most directly on online forms of political engagement, where citizens face a choice between using internet access for political or non-political purposes. Its implications for offline participation depend on whether online and offline political engagement are substitutes or complements: if they are substitutes, a decline in online political activity may free time or motivation for offline participation; if they are complements, reduced online engagement may spill over into lower offline participation as well. Which of these countervailing forces dominates is unlikely to be uniform across all forms of political engagement, and may depend critically on the costs and informational demands each subtype places on citizens.

In this study, we focus on three dimensions of political participation: in-person participation, electoral participation, and online participation. In-person participation encompasses attendance at community and ward meetings and direct contact with local officials to raise grievances. Here, the cost-reduction and substitution mechanisms point in opposite directions. Internet access may increase such participation by lowering the coordination costs of organizing collective action and enabling rapid diffusion of mobilization appeals. At the same time, if online engagement substitutes for offline activity, internet access may reduce the motivation to participate in-person by offering lower-cost expressive alternatives that satisfy political impulses without requiring physical presence. The existing theory therefore points to competing expectations.

For electoral participation, the nationalization mechanism and the cost-reduction mechanism similarly generate competing expectations. Easier access to information about candidates and procedures may lower barriers to voting, particularly among low-information citizens. Yet if internet access shifts attention toward national political narratives at the expense of local politics, its effect on turnout may vary across electoral levels, strengthening engagement with national contests while attenuating participation in local ones. Here too, the direction of the effect is an empirical question.

Online participation, including contacting officials through digital channels and engaging with government and party social media pages, is most directly enabled by internet access. Unlike in-person and electoral participation, the barriers to online political acts are low even without strong political motivation, and internet access removes them further. Following this logic, we pre-registered a one-sided hypothesis that internet access increases online political participation, though we noted that the magnitude of this effect may depend on the broader information environment and the degree to which online platforms channel engagement toward political rather than entertainment content.

The Second Stage of Internet Expansion

A less studied aspect of internet access is how its political effects vary depending on the stage of connectivity expansion. While existing studies have been essential for understanding the political consequences of the first stage of internet adoption—the transition from being offline to being online—they do not capture the full range of changes currently underway across the Global South. Connectivity has expanded dramatically over the past three decades, and over one-third of the Sub-Saharan African population now uses the internet, even after excluding high-income countries.[1] Yet for many users, engagement remains constrained by strict data caps that limit sustained or data-intensive use. A second stage of internet expansion based on fiber broadband is now underway to address these limitations. Across Africa, fiber broadband subscriptions reached 4.7 million in 2022 and are projected to nearly triple by 2028 (Reed, Mbongue and Njue 2023). The change in this transition lies not in whether people are connected, but in how connectivity is expanded from constrained mobile data to uncapped home access.

What distinguishes the second stage of expansion from the initial wave is the technological environment into which it is introduced. In many industrialized countries, high-speed home broadband preceded the widespread adoption of mobile internet. In contrast, in much of the developing world, mobile internet became widespread first, often under tight data con-

[1]https://data.worldbank.org/indicator/IT.NET.USER.ZS

straints, with fixed home connections introduced later (Aker and Mbiti 2010; International Telecommunication Union 2023). These modes of access differ along three politically relevant dimensions: portability, data constraints, and spatial anchoring. Mobile internet–characterized by limited data and intermittent use–has been shown to facilitate communication, coordination, and collective action, including protests (Manacorda and Tesei 2020; Enikolopov, Makarin and Petrova 2020; Christensen and Garfias 2018). Home broadband, by contrast, allows for more sustained and less constrained use and is more strongly associated with entertainment consumption (Falck, Gold and Heblich 2014). Evidence from industrialized settings suggests that the expansion of home broadband can therefore have secondary effects that differ from those of initial internet access, including potential declines in political participation (Campante, Durante and Sobbrio 2018; Falck, Gold and Heblich 2014). However, this literature largely examines contexts in which fixed broadband represented the first major expansion of internet access. We know far less about settings where mobile internet is already widespread and home broadband constitutes a second-stage technological shift. Home broadband is increasingly being rolled out in the Global South, yet its political effects in mobile-saturated contexts remain poorly understood.

We argue that in mobile-saturated Global South contexts, the expansion of home internet operates through a distinct mechanism: a reallocation of time toward the home. Because fixed broadband increases the returns to remaining at or near the dwelling, it may alter daily routines, particularly in settings characterized by unemployment, informality, and flexible time allocation. Unlike information-based mechanisms, this channel does not primarily operate through changes in content exposure but through changes in the spatial organization of everyday life.

The mechanism operates in two primary steps. First, fixed broadband increases the utility of remaining at home relative to other locations. Second, increased time at home can raise locally oriented political engagement through two sub-channels. One operates through *grievance exposure*: physical presence in the household heightens direct awareness of service-delivery failures—electricity outages, water disruptions, sanitation problems—that provide concrete reasons to contact local officials. The other operates through *social exposure*: proximity to one's community raises the likelihood of encountering ward and community meetings and of interacting with neighbors who share information about local issues. These sub-channels are not mutually exclusive but generate distinguishable empirical signatures: if the grievance-exposure channel dominates, effects should concentrate in complaints about service delivery; if the social-exposure channel dominates, effects should appear in meeting attendance and neighborhood-level engagement. A third channel may also operate: continuous access to hyper-local digital networks—such as community WhatsApp groups and local social media pages—could lower the coordination costs of collective action (Christensen and Garfias 2018; Manacorda and Tesei 2020), though as we discuss below, we find no evidence that the treatment increased participation in community or family WhatsApp groups. Rather than primarily nationalizing political attention—a pattern often emphasized in high-income democracies (Hopkins 2018)—home internet in these settings may reinforce place-based engagement rooted in service delivery and local governance concerns.

The magnitude of these effects should depend on individuals' baseline time allocation. Individuals who already spend substantial time at home are likely to experience smaller marginal changes in exposure to local conditions. In our study context, gender is a strong predictor of time spent outside the home: men are more likely to be away from the household due to lower rates of unemployment relative to women (43% vs. 62% at baseline), fewer caregiving responsibilities, and greater tendency to socialize or search for work outside the household. We therefore expect the treatment effect on local political engagement to be larger among men, who have the most room for the intervention to shift time toward the home.

This framework yields two main empirical implications. First, the political effects of home internet in mobile-first contexts should differ from those observed following initial mobile access or broadband expansion in industrialized democracies. Second, home internet access should have stronger effects on local forms of political participation—such as attending community meetings and contacting local officials—than on national electoral turnout.

By distinguishing between modes of access and emphasizing spatial mechanisms, this framework clarifies why the political consequences of internet expansion may vary systematically across institutional and economic contexts.

3 Study Design

In this section, we describe our empirical strategy. We begin by describing the study context of South Africa and the study township. We then detail the experimental design, including the intervention, sampling strategy, random assignment, outcome measurement, and estimation strategy.

Context

Internet access: Internet access in South Africa is highly unequal. Whereas uncapped home internet connections are common in high-income neighborhoods, residents of low-income townships have largely relied on mobile data for internet access. According to the 2020 General Household Survey, fewer than 10% of households with members aged 5 to 24 access the internet through a home connection. As a result, most township residents depend on mobile data, which is considerably more expensive. The average price of 1GB of mobile data is approximately $1.81 USD, placing South Africa 149th out of 237 countries in terms of data affordability. These high costs have generated widespread dissatisfaction and political mobilization. One prominent example is the #DataMustFall campaign, which emerged as a national movement protesting the high price of mobile data and demanding more affordable internet access, framing connectivity as essential for economic and educational opportunity. At the same time, fiber home internet has increasingly been rolled out in some townships in recent years. We return to this point later when discussing treatment take-up and compliance.

Political climate: Our study was conducted in the period surrounding the 2024 national elections. South Africa elects its National Assembly through a party list system of proportional representation. The African National Congress (ANC) has governed the country since the end of apartheid in 1994, yet its electoral dominance has steadily eroded. The 2024 election marked a critical turning point as the party lost its absolute majority for the first time. Following the election, the ANC formed a coalition government with the Democratic Alliance (DA) and two additional parties, with seven smaller parties joining the coalition at a later stage.

The election period was also marked by the emergence of the MK Party, a populist left-wing party led by former president Jacob Zuma. Since its formation in 2023, the party gained substantial support in KwaZulu-Natal province—where our study took place. The MK Party has frequently been described as drawing on Zulu nationalist appeals, which resonated strongly in a province where Zulus constitute the largest ethnic group. In the 2024 KwaZulu-Natal provincial election, the party secured 1.59 million votes, equivalent to 45.35% of the total, and won 37 of the 80 seats in the provincial legislature. As a result, the ANC was relegated to third place in what had previously been one of its strongest regional bases.

Levels of government: South Africa operates under a three-tier system of government comprising national, provincial, and municipal levels. Municipalities are responsible for the provision of basic services such as electricity, water, sanitation, and waste removal. Within municipalities, ward councilors represent the lowest level of elected office. These councilors sit on municipal councils and exercise substantial influence over local governance, particularly in low-income townships. Because of their proximity to residents, they are often well known within their communities.

Study township: The study site is a predominantly Black township in KwaZulu-Natal province with an estimated population of 51,000 residents. The township faces significant socioeconomic challenges. The median household income is roughly 75% of the national median, and unemployment is estimated to be as high as 63%. Residents also experience persistent failures in basic service provision, including frequent disruptions to roads, sewerage, water, and electricity. Crime rates are high, with 289 reported assaults in 2024 alone. Politically, the ward councilors in the township are affiliated with the ANC. Local familiarity with these officials is substantial as 60% of respondents in the baseline survey were able to correctly identify their ward councilor by name. Access to home internet remains limited, with only 15% of households reporting a fixed home connection at baseline.

Intervention

Our intervention leverages a network of pre-existing Wi-Fi hotspots that our partner organization, Project Isizwe, installed in the study township. Access to these public Wi-Fi hotspots requires residents to pay a daily fee of 5 Rand (approximately $0.29). Households in our treatment group are provided with a router that can connect to the nearest public Wi-Fi hotspot. This allowed individuals with an internet-capable device to have uncapped internet access without the standard R5 payment. Household members were told that the free internet access was a promotional offer that would expire at a set date after the outcome measurement. Once the free access expires, household members can still access the internet through the routers, but it will cost them 5 Rand a day. The model is a pre-paid model—in other words, users only pay for the internet they use and cannot incur a debt.

The Wi-Fi routers were installed between January 9 and May 7, 2024 (a detailed description of installation and maintenance procedures is provided in Appendix A.2). During installation, the technician explained how to access the internet through the router, gave instructions on managing the connection, and shared contact information for additional assistance. To support timely communication, the team created a WhatsApp group with the participating households, which allowed recipients to reach the team quickly when questions arose. Household members were also informed that the router would remain in place unless they chose to discontinue the service, in which case Project Isizwe would remove it upon request.

Upon installation, Project Isizwe registered the phone number of the main respondent interviewed at baseline (see below) to the router and allowed them to choose up to two additional household members to be connected. To ensure that only members of the participating household could use the connection, internet access was restricted to these three registered numbers. Each time a user connected to the Wi-Fi, a browser window appeared requesting entry of the registered phone number before granting access. Recognizing that many respondents had multiple electronic devices capable of connecting to Wi-Fi, we allowed devices other than smartphones—such as tablets or laptops—to connect to the network as well. However, only one device linked to a given registered number could be online at a time to maintain controlled access.[2]

Sampling and baseline survey

Our study draws on a convenience sample of 400 households surveyed at baseline in August and September 2023. Our sampling strategy was designed to minimize the possibility of spillovers. Spillovers were a central concern for the internet access treatment because members of nearby control households could potentially use a neighbor's router to go online. This risk was amplified by the township's high population density and the fact that routers could only be installed in specific parts of the township (hereafter, *coverage area*). Since the routers connected households to existing public Wi-Fi hotspots, the boundaries of the coverage area were determined by the placement of those pre-existing hotspots.

To address these concerns, our sampling strategy followed three steps. First, Project Isizwe provided geolocations for all dwellings in the township where installing a Wi-Fi router was feasible. From this set, we selected 500 households using a procedure that maximized the minimum distance between any two selected households.[3] Given the high density and small size of the coverage area, the largest minimum distance that still allowed us to select at least 500 households was 39 meters.[4]

Second, we pre-assigned each selected household a target gender for the respondent to be enrolled (250 female and 250 male respondents) to ensure a balanced sample. Third, enumerators visited all 500 households. During each visit, enumerators listed all household members who met the following criteria: (a) the individual matched the gender preassigned to the household, (b) was between 18 and 34 years of age, (c) held South African citizenship, and (d) was either part of the family that owned the dwelling or, if renting, intended to remain at the dwelling

[2]Residents often have multiple phone numbers, and number changes are common. To accommodate this, households were allowed to update their registered numbers upon request by contacting Project Isizwe through phone or WhatsApp. While updating the registered number is possible, the number of registered phone numbers must always remain at three. If a user wishes to add a new number, they must remove one of the existing numbers from the list.

[3]This procedure relied on a C++ algorithm that (a) selects at least 500 geolocations and (b) ensures that every pair of selected households is separated by at least k meters. The code is included in the replication materials.

[4]Although our target sample size was 400 households, we oversampled at the first stage to account for possible non-response or ineligibility.

for at least the next six months.

If at least one household member met these criteria, the household was enrolled in the study. When only one eligible member was present, that individual became the baseline respondent. When multiple eligible members were present, enumerators used the survey tablet to randomly select the respondent from the eligible set. If no eligible person resided in the household, enumerators proceeded to the nearest neighboring dwelling and repeated the procedure. If the replacement household was also ineligible, they continued to the next closest dwelling, and so on, until an eligible household was identified.

In total, we collected baseline data for one respondent in each of the 479 households. The baseline survey included a question asking whether the household would be interested in receiving a Wi-Fi router as part of a hypothetical NGO program.[5] To narrow this group to the target sample of 400 respondents, we excluded individuals based on the following criteria: (a) residence in areas identified by the field team as potentially unsafe for data collection, (b) recorded gender that did not match the preassigned gender, (c) stated lack of interest in receiving a free home Wi-Fi router with unlimited internet access, and (d) residence in locations that Project Isizwe determined after baseline were difficult or impossible to reach with Wi-Fi coverage.

Applying these exclusions resulted in a final study sample of N = 400 respondents across 400 households. Appendix Table **??** shows that our final study sample is balanced on gender (50% female), is evenly distributed across age groups from 18 to 34, and predominantly Zulu (72%). The majority of households have at least five members. Most respondents have access to an internet-capable device (85% have access) though only 22% have a home internet connection. In terms of baseline political engagement, 26% of the respondents reported engaging in political activities either in-person or online, 43% voted in the last national election in 2019, and 33% voted in the previous municipal election in 2021.

[5] To avoid revealing the purpose of the study, this question was presented alongside items about other NGO programs commonly offered in South Africa.

Random assignment

We randomly assigned 200 of the 400 study households to receive a home Wi-Fi router. We first formed 200 matched pairs of similar households using longitude and latitude, baseline measures of respondents' political knowledge, gender, access to an internet-capable device, and political engagement both in-person and online. We then randomly assigned one unit in each pair to treatment and the other to control (for a detailed description of the blocking procedure, see Appendix A.4). We cross-randomized a second treatment in the form of series of encouragement text messages to visit a Facebook-based get-out-the-vote (GOTV) campaign that were sent to the main respondent in a randomly chosen set of 200 households. This assignment was blocked by the assignment to the internet treatment, i.e., we assigned exactly 100 households that were also assigned to Wi-Fi router and 100 households not assigned to the router to the GOTV treatment. All analyses in this paper marginalize across the GOTV treatment. Appendix A.5 provides further details.

Treatment take-up and compliance

Among the 200 households assigned to treatment, 156 (78%) received a router. Two households that did not belong to the treatment group received routers. Yet, the contact information of these households does not match any information of households in our control group. Hence, we assume that all households in the control group complied with their assigned treatment status and that non-compliance is one-sided.

The most likely reason for non-compliance is that households in our study sample may have obtained internet access through other sources unrelated to this project during the study period. The study township had relatively limited internet infrastructure at baseline, but fiber internet nonetheless became increasingly available in parts of the township during the study period. The availability of fiber connectivity may have reduced the attractiveness of the study-provided routers, though it is important to note that access to fiber required households to pay for the service whereas the study-provided routers were free.

Administrative usage data from Project Isizwe provide additional evidence on treatment intensity. Figure A.6 in the Appendix plots average daily data consumption (GB) through the intervention router by study week across households assigned to treatment, with the number of households that generated any traffic in each week reported in parentheses after the week labels. The figure indicates substantial data use among households that actively used the router, but also shows that the share of households using the router in a given week was relatively low. Overall, of the 156 households that received a router, 136 used it in at least one study week and 99 used it in more than 10 weeks. This pattern suggests that limited take-up over time may reflect technical or connectivity frictions beyond initial installation, which could attenuate effects on internet-mediated outcomes, while still implying meaningful increases in internet access for a sizable subset of treated households.

Outcome measurement

We measured outcomes using a post-election survey and an endline survey, which we describe in turn. The first outcome of interest is turnout in the 2024 South African national election. The use of indelible thumb ink in South African elections provided a rare opportunity to validate self-reported turnout with a visible physical marker of voting. A key strength of this measurement strategy is its ability to mitigate social desirability bias, in which individuals may claim to have voted even when they have not because voting is widely viewed as a socially expected behavior. Since the ink remains visible for only a few days, twenty enumerators visited each study household within three days of the national election on May 29, 2024 to verify the turnout of the main respondent interviewed at baseline.[6] After confirming the respondent's age and gender to verify that the correct individual from the baseline was being interviewed, enumerators asked whether the respondent had voted and, if so, requested to see the inked thumb and to photograph it. In total, enumerators managed to verify the turnout of 290 out of 400 baseline respondents for a response rate of 72.5%.

To measure a broader set of outcomes, we conducted an endline survey from January 30 to

[6]Because of security concerns on election day, visits began the following day to ensure enumerator safety.

March 23, 2025. For the endline survey, we re-interviewed the original respondents and interviewed one additional randomly sampled household member of the opposite gender between the ages of 18 and 65.[7] This yielded a total of $N = 562$ respondents in the endline survey for a 70% response rate. As shown in Appendix A.6, we find no evidence of differential rates or patterns of attrition for the endline survey. Enumerators were not involved in implementing or monitoring the Wi-Fi intervention and were therefore blind to respondents' treatment assignment. The purpose of the endline survey and the specific hypotheses being tested were also not disclosed to the enumerators.

Estimation

Our primary quantities of interest are the sample intent-to-treat effects (ITTs) of the Wi-Fi router intervention among respondents in our study population. The unit of analysis is the respondent. We estimate sample ITTs using the following pre-registered OLS regression specification:

$$y_{ij} = \alpha + \tau z_j + \beta' \mathbf{x}_j + \epsilon_{ij}$$

where y_{ij} is the outcome for respondent i in household j; α is an intercept; τ is the ITT among the respondents in the sample; z_j is an indicator for whether household j was assigned to treatment; $\mathbf{x}_j$ is a vector of four pre-specified covariates for household j and β' is transposed vector of associated coefficients; ϵ_{ij} is an error term for respondent i in household j.[8] Most analyses include two respondents per household. Hence, for most analyses, we adjust our variance estimates to allow for the clustering of the error term ϵ_{ij} on the household level. In analyses that use only one respondent per household, we do not cluster standard errors but continue to use heteroskedasticity-robust estimates. All analyses and the direction of

[7] If no household member met these eligibility criteria, enumerators randomly selected a permanent household member of the same gender as the baseline respondent. In single-member households, only the baseline respondent was interviewed.

[8] We will report estimates from barebones specifications that do not control for covariates as a robustness check in the Appendix.

hypothesis tests follow our pre-registration unless noted otherwise. p-values are calculated using randomization inference (RI) using pre-registered permutation matrices with $10,000$ permutations. Additional details on the pre-registered covariates and estimation of heterogeneous effects are provided in Appendix A.7.

4 Main Results

We now examine how access to a Wi-Fi router influences political participation. Table 1 presents the results. The outcome in column 1 is an index constructed from survey items asking whether the respondent attended meetings with their community, Ward councilor, or a political party, and whether they contacted their Ward councilor, municipality, or a political party in-person to raise an issue. We classify contact as in-person if the respondent reports any of the following actions: (a) visiting the office in-person, (b) calling the office, (c) asking another person to make contact on their behalf, or (d) specifying another method of contact that does not involve the internet. The Wi-Fi router treatment increased respondents' in-person political participation by 0.04 scale points, an estimate that is equivalent to roughly 0.17 standard deviations of the outcome in the control group ($p < 0.05$). Given that the control mean is 0.23, an increase of 0.04 represents an 18% increase over the average level of in-person participation in the control group.

The outcome in column 2 is an indicator for whether the respondent reported having voted in the 2024 national election during the endline survey. While turnout was more than six percentage points lower in the treatment than in the control group, this difference is imprecisely estimated and does not reach statistical significance.[9]

[9]These findings will be replicated in the Appendix using data from our midline turnout verification exercise. Across a number of alternative pre-registered codings of the outcome, we find that the home router treatment, if anything, had a negative effect on turnout.

Table 1: Effect of home Wi-Fi access on political participation

	In-person participation	Has voted in 2024	Online participation
WiFi	0.042**	-0.065	-0.014
	[0.020]	[0.043]	[0.011]
Outcome range	[0,1]	[0,1]	[0,1]
Control SD	0.250	0.496	0.163
Control mean	0.228	0.570	0.139
Hypotheses	two	two	upr
Observations	562	562	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *In-person participation* is an index capturing whether respondents attended community, Ward, or party meetings in the past 12 months and whether they contacted these actors in person to raise an issue. *Has voted in 2024* indicates whether the respondent reports voting in the 2024 national election; results are the same when using the thumb print verified measure available for part of the sample. *Online participation* is an index measuring whether respondents complained to the Ward, municipality, or party online and how much they interacted with their Facebook pages.

The outcome in column 3 is an index constructed from survey items measuring whether respondents reported contacting their Ward councilor or Ward committee officials, municipal officials including the mayor, or a local political party branch through online channels, as well as whether and how much they interacted with the Facebook pages of the ward, municipality, or political party. We classify contact as online if the respondent reports any of the following actions: (a) sending an email, (b) using a contact form on an official website, (c) contacting officials on Facebook including tagging them in a post, (d) sending a WhatsApp message, or (e) specifying another method of contact that involves the internet. For Facebook engagement, the outcome is coded as 0 if the respondent has not visited the Facebook page, 0.5 if the respondent has visited the page but does not follow it and has not reacted or posted, and 1 if the respondent follows the page or has reacted or posted. The index is constructed by averaging across the six items. Likewise, we find no evidence that access to a Wi-Fi router increases online political engagement. The Wi-Fi router decreased respondents' online political participation by 0.01 scale points, yet this difference is not statistically distinguishable from zero. This null result contradicts our pre-registered expectation—tested with a one-sided hypothesis—that home internet access would increase online political participation.

Taken together, our findings suggest that access to a home router has limited effects on voter turnout and online political participation, but significantly increases in-person political participation. Given that the in-person political participation index captures engagement across multiple levels of governance, we next disaggregate this index to identify which specific components are affected by the treatment. We organize the disaggregation by level of governance, distinguishing items related to one's community and Ward councilor (*Local*), one's municipality (*Municipal*), and political parties (*Party*). This allows us to assess whether the treatment effect is concentrated at specific governance levels.

Table 2: Effect of home Wi-Fi access on in-person political participation

	In-person participation		
	Local	Municipal	Party
WiFi	0.055**	0.067**	0.010
	[0.026]	[0.029]	[0.026]
Outcome range	[0,1]	[0,1]	[0,1]
Control SD	0.306	0.290	0.335
Control mean	0.293	0.093	0.202
Hypotheses	two	two	two
Observations	562	561	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). This table disaggregates the *In-person participation* index into its constituent governance levels. *Local* captures attending community or ward councilor meetings and complaining to ward officials in person. *Municipal* captures complaining to the municipality or mayor in person. *Party* captures attending party political meetings and complaining to political parties in person.

Table 2 summarizes the results. We find that access to a Wi-Fi router increases in-person political activity particularly within one's locality. Respondents who received a home router exhibit higher levels of attendance at community meetings and visits to Ward councilors, with an estimated increase of 0.06 scale points, equivalent to approximately 0.18 standard deviations of the control group outcome ($p < 0.05$). These respondents also report more complaints to municipal offices than those in the control group, with an estimated increase of 0.07 scale points, or 0.23 standard deviations of the control group outcome ($p < 0.05$). In-person engagement with political parties increases as well, although the estimated effect is not statistically distinguishable from zero. With these findings in mind, we now turn to the mechanisms that may account for the observed increase in local in-person political participation.

5 Mechanisms

The preceding results raise a puzzle: why does home internet access increase in-person political participation yet leave online participation unchanged? We now investigate mechanisms that may explain this pattern. Because the analyses in this section are exploratory, we report two-sided hypothesis tests throughout.

Effects on internet usage. Before turning to mechanisms, we address a primary concern: the null effects on online participation might simply reflect poor implementation of the Wi-Fi treatment rather than a substantively meaningful pattern. We assess treatment take-up using five measures of internet use: (a) time spent online, derived from respondents' reports of how they spent a randomly selected day in the previous week using three-hour time windows; (b) use of the study router and (c) internet access, both self-reported; (d) ownership of an internet-capable device; and (e) average time since a respondent was last active on WhatsApp, based on periodic checks of online status conducted after the endline survey. Columns 1, 3, and 4 of Table 3 show that treated households spend significantly more time online and are more likely to use a home router to connect to the internet. CACE estimates among compliers (Table C.14 in the appendix) indicate that these effects are sizeable, on the order of 0.15–0.20 standard deviations of the control group outcomes. The treatment thus meaningfully increased internet access, confirming that the null results for online political participation are not an artifact of failed implementation.

Table 3: Internet usage outcomes for treatment and control groups

	Time online	Uses home router	Internet usage	Owns device	Last seen on WhatsApp
WiFi	0.104**	0.072**	0.074**	-0.016	0.084
	[0.059]	[0.039]	[0.042]	[0.016]	[0.417]
Outcome range	log(1 + hours)	[0,1]	[0,1]	[0,1]	log(1 + minutes)
Control SD	0.696	0.417	0.499	0.184	2.424
Control mean	0.591	0.222	0.544	0.401	4.958
Hypotheses	upr	upr	upr	upr	lwr
Observations	561	562	562	562	137

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Time online* is the log-transformed total hours spent using the internet (in 1.5 hour increments), measured via a time use survey. *Uses home router* indicates whether the respondent uses a home Wi-Fi router to access the internet. *Internet usage* is a self-reported indicator of using the internet more than once per day. *Owns device* is an index of smartphone, tablet, and computer ownership. *Last seen on WhatsApp* is the average log-transformed time (in minutes) since last WhatsApp activity, measured via metadata tracking; lower values indicate more recent activity.

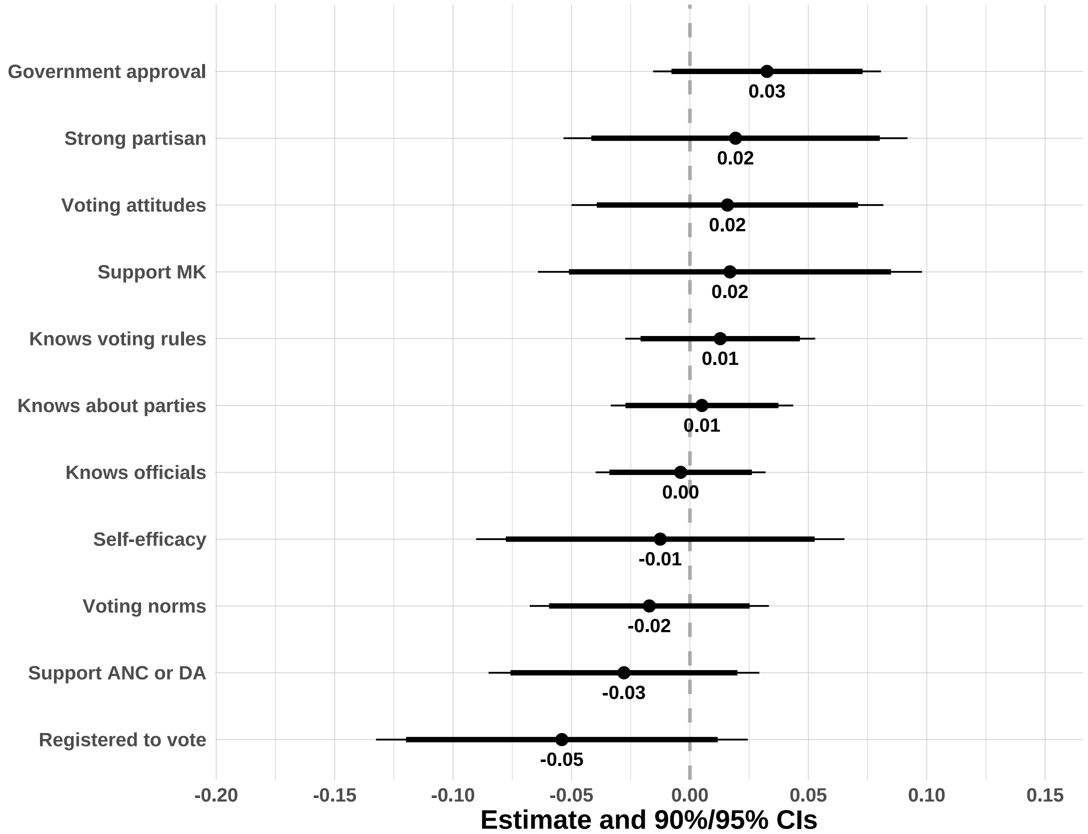
Shift in political beliefs and media exposure. A potential explanation for the increase in in-person political participation is that home internet access may have shifted respondents' political beliefs and media exposure. A large literature shows that internet affects political attitudes and knowledge by expanding information channels, lowering barriers to interaction, and reducing incentives for preference falsification (see Farrell (2012) and Zhuravskaya, Petrova and Enikolopov (2020) for overviews). Internet access can also shift patterns of news consumption by substituting for traditional media such as newspapers or television. Changes in where people obtain news alter the (mis)information they encounter, with potential consequences for how people develop political views. If the Wi-Fi treatment altered respondents' political attitudes, political knowledge, or their main news sources, these shifts may have influenced how they engage with local politics.

We assess this possibility by first examining whether the Wi-Fi treatment affects a set of outcomes that capture respondents' political attitudes and knowledge. We consider four domains. The first is partisan preference, which includes strong partisanship and support for the country's three prominent parties: the ANC (African National Congress), DA (Democratic Alliance), or MK (uMkhonto weSizwe).[10] The second is political evaluations and efficacy,

[10] ANC (African National Congress) originated during the struggle against Apartheid and has formed the

measured through government approval and self-efficacy. The third concerns voting attitudes and behaviors, including voting norms, voting attitudes, and voter registration. The fourth captures political knowledge, assessed through respondents' knowledge of political parties, voting rules, and public officials. Appendix B.1 presents the questionnaire used to measure each of these outcomes.

Figure 1: Effect of home Wi-Fi access on political attitudes and knowledge



As shown in Figure 1[11], we find no evidence that access to a Wi-Fi router affects political attitudes or knowledge. Across the full set of outcomes ranging from partisan preferences to voting behavior, the estimated effects are not statistically distinguishable from zero. Measures

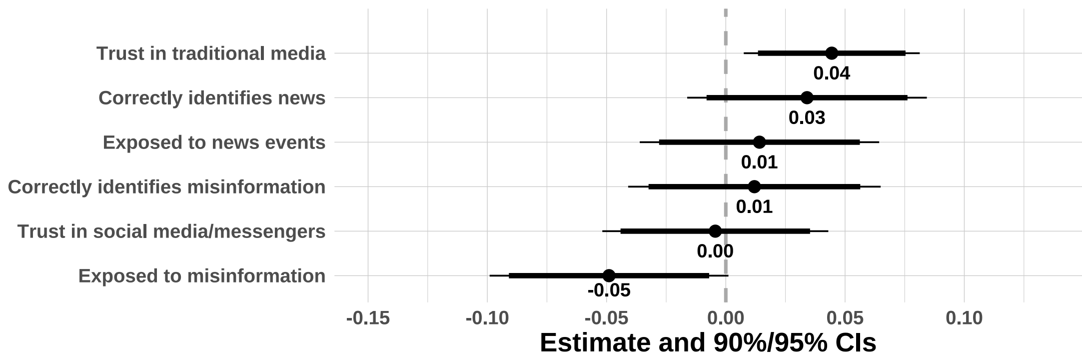
country's government since 1994. DA (Democratic Alliance) used to be the most important opposition party, now part of the coalition government. The MK Party is a relatively new left-wing populist party linked to former president Jacob Zuma.

[11]See Appendix B.2 for the corresponding results in table format.

of political knowledge likewise show no significant effects, and the direction of the estimates varies across indicators.

We next examine the effect of Wi-Fi treatment on media exposure. For this analysis, we focus on three domains. The first is news exposure, which captures whether respondents encountered recent news events or misinformation. The second is information accuracy, measured through respondents' ability to correctly identify factual news and misinformation. The third concerns media trust, assessed through trust in traditional media and trust in social media or messaging platforms. A detailed description of how each measure was constructed and the wording of the questionnaire appears in Appendix B.1.

Figure 2: Effect of home Wi-Fi access on media exposure



Note: The first four outcomes are constructed by confronting respondents with four (three) actual news (misinformation) headlines and asking them whether they have seen these (exposure) and whether they are correct (correctly identifies).

Figure 2 presents the results. Respondents in the Wi-Fi treatment group reported significantly lower exposure to misinformation. When asked to evaluate whether specific news headlines were accurate, respondents in households that received the router also showed a marginally higher rate of correctly identifying truthful news. These findings are somewhat counter-intuitive given the substantial literature emphasizing that online environments often increase exposure to misinformation, where formal fact-checking is limited and false content circulates rapidly. Contrary to expectations, we further find that respondents in the Wi-Fi treatment group expressed significantly higher trust in traditional news sources, such as television and radio, compared to those without access to the router. This finding is once again surprising given that much of the existing literature emphasizes how online environments can erode trust in established traditional media.

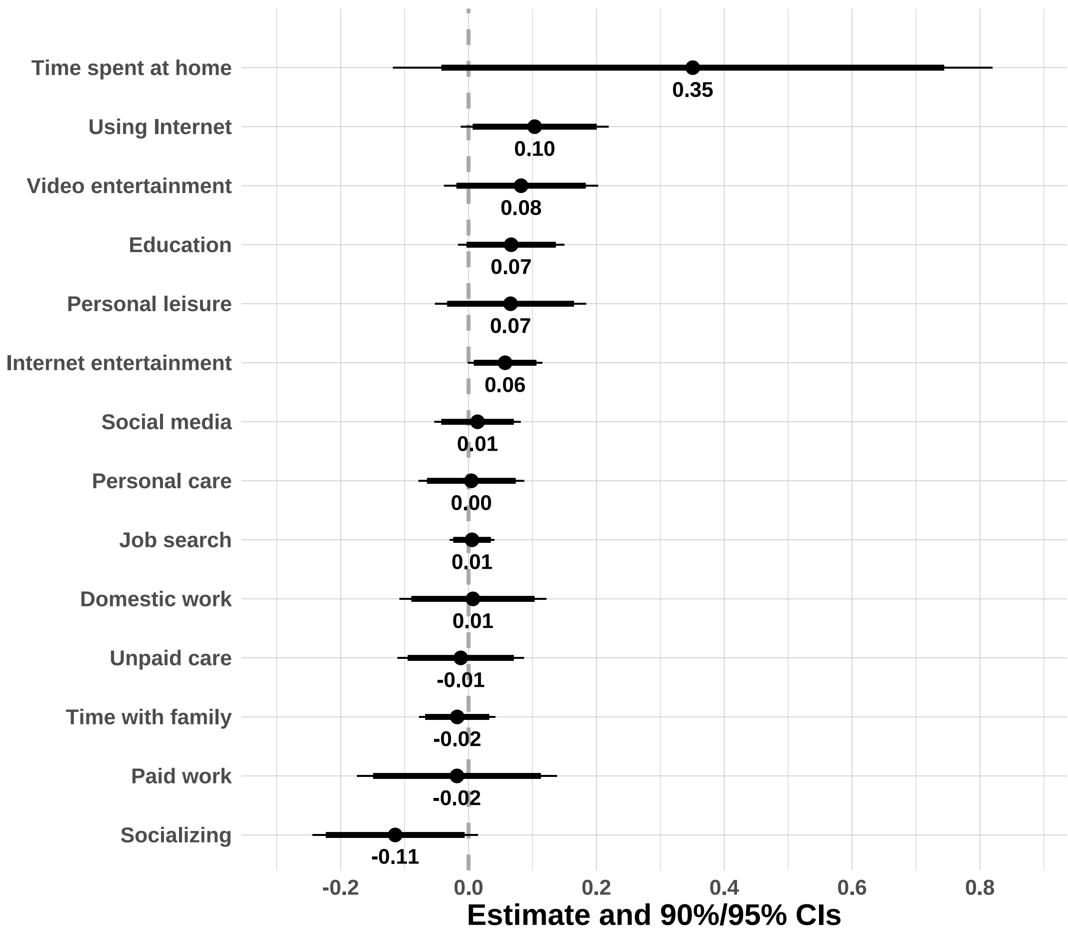
In fact, the news consumption patterns we observe point toward a greater emphasis on respondents' local community environment rather than increased exposure to news from online sources. Additional analyses disaggregating news type show that respondents with access to a Wi-Fi router had significantly higher rates of correctly identifying truthful news for local and provincial headlines, but not for national ones (see Appendix Table B.5 for full results). Rather than exhibiting an increase in online news consumption, respondents in the Wi-Fi treatment group reported consuming more news through conversations with family, friends, and neighbors, as well as through community meetings.

Taken together, we find no evidence that access to a home Wi-Fi router affects political attitudes, knowledge, or patterns of online news consumption. These results allow us to rule out the possibility that the observed increase in local in-person participation is driven by shifts in respondents' political beliefs or their exposure to online media. Instead, the evidence indicates that the treatment increased interactions with family and community members. We also find no evidence that the treatment increased participation in community or family-and-friends WhatsApp groups, suggesting that the coordination channel emphasized in some accounts of mobile internet and collective action does not appear to be operative in this context. We therefore next examine whether the Wi-Fi treatment increased local political participation by influencing how people structured their daily activities.

Changes in time spent at home. A second channel through which home internet access may influence political participation operates through the physical constraints of the connection itself. Because the router provides internet access only within the home, individuals cannot use the uncapped connection once they leave the household. This spatial boundedness could create an incentive to spend more time at home or in the immediate neighborhood, which in turn may increase incidental exposure to local politics. Several pathways could link greater time at home to in-person political engagement. Proximity to one's community may raise the likelihood of encountering Ward and community meetings, which typically take place in nearby public spaces, and of interacting with neighbors who share information about local issues and public services. Time spent at home may also increase exposure to television and radio broadcasts that carry locally relevant political content. Finally, physical presence in the household could heighten awareness of service-delivery failures—electricity outages, water disruptions, or sanitation problems—that provide concrete reasons to contact local officials. If this mechanism is operative, we should observe that the treatment shifts time use toward the home and that these effects are concentrated among individuals who would otherwise spend substantial time outside the household. For this reason, we expect the treatment effect to be stronger for men.

Figure 3 provides suggestive evidence in line with this mechanism. Home Wi-Fi access marginally increases time spent at home and marginally decreases time spent socializing, suggesting that the router encourages respondents to remain in or near the household. Regression tables corresponding to all figures in this section appear in Section B.2.

Figure 3: Effect of home Wi-Fi access on time spent at home

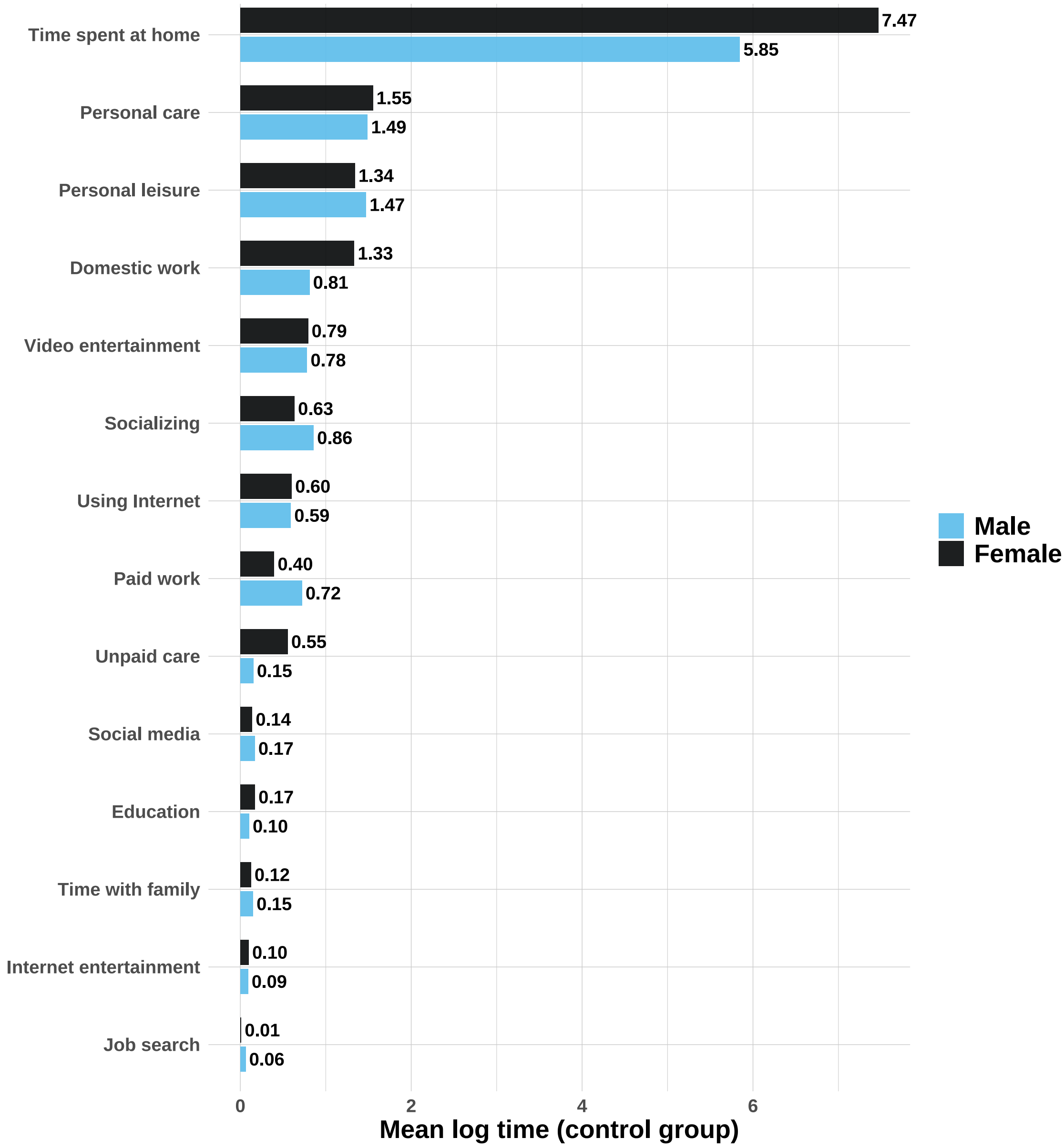


Note: All measures derived from respondents' open-ended reports in three-hour windows of how they spent a randomly chosen day in the previous week.

Disaggregating the in-person participation index into its constituent items (Table B.11 in Section B.2) reveals that the positive effects are concentrated in complaints to ward and municipal officials—the latter equivalent to approximately 0.23 standard deviations of the control group outcome ($p < 0.05$)—rather than in attendance at community meetings. This pattern is more consistent with heightened awareness of service-delivery failures at home than with increased exposure to community meetings or neighborhood networks.

Heterogeneity by gender. If the mechanism operates through increased time spent at home, the treatment effect should be larger among individuals who would otherwise spend substantial time outside the household. Figure 4 confirms the descriptive basis for this prediction: in the control group, men report spending substantially less time at home than women, consistent with their lower rates of unemployment (43% vs. 62% at baseline), fewer caregiving responsibilities, and greater tendency to socialize or search for work outside the household. Given these baseline differences, we expect men to exhibit a larger treatment effect.

Figure 4: Time usage disaggregated by gender



Note: All measures derived from respondents' open-ended reports in three-hour windows of how they spent a randomly chosen day in the previous week.

Table 4 shows that the treatment effect on in-person participation is indeed concentrated among men: the estimated effect for men is 7.6 percentage points, or approximately 0.30 standard deviations of the control group outcome ($p < 0.05$), while the interaction with gender is negative and of comparable magnitude (6.1 p.p., $p > 0.10$), implying a near-zero effect among women. Although the interaction term is not statistically significant—the analysis is underpowered for detecting heterogeneous effects—the direction is consistent with a mechanism operating through changes in time use. Disaggregating time use by gender (Table B.9 in Section B.2) further supports this interpretation: the treatment significantly increases time spent on internet entertainment among men ($p < 0.05$), an effect that is fully offset among women ($p < 0.10$). Notably, the increase in internet entertainment among men coexists with their increase in in-person participation, suggesting that entertainment substitution did not crowd out offline political engagement in this context. The time-use channel appears to dominate: home internet brought men home and kept them there, increasing both entertainment consumption and incidental exposure to local grievances and governance activities.

Table 4: Effect of home Wi-Fi access on in-person political participation by gender

	In-person participation	Voted in 2024	Online participation	Time spent at home
WiFi	0.076**	-0.082	0.002	0.391
	[0.031]	[0.061]	[0.019]	[0.338]
Woman	0.022	0.067	0.012	1.610***
	[0.028]	[0.058]	[0.021]	[0.323]
WiFi x Woman	-0.061	0.038	-0.029	-0.196
	[0.041]	[0.079]	[0.028]	[0.441]
Outcome range	[0,1]	[0,1]	[0,1]	log(1 + hours)
Control SD	0.250	0.496	0.163	2.753
Control mean	0.228	0.570	0.139	6.675
Hypotheses	two	two	two	two
Observations	558	558	558	558

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on parametric standard errors. *In-person participation* is an index capturing whether respondents attended community, Ward, or party meetings in the past 12 months and whether they contacted these actors in person to raise an issue. *Voted in 2024* indicates whether the respondent reports voting in the 2024 national election. *Online participation* is an index measuring whether respondents complained to the Ward, municipality, or party online and how much they interacted with their Facebook pages. *Time spent at home* is the log-transformed total minutes spent at home, measured via a time use survey.

6 Conclusion

This paper provides novel evidence on the political effects of expanding *home* internet access in a context where mobile connectivity is already widespread but data are costly. In a pre-registered field experiment in a low-income South African township, offering households uncapped home Wi-Fi did not increase voter turnout, online political participation, political knowledge, and did not lead to broad shifts in political attitudes. Instead, it increased *in-person* participation, particularly in place-based engagement with local governance: attendance at community and ward meetings and complaints to ward and municipal officials.

The pattern of results points away from an information-only account of internet effects and toward a behavioral mechanism tied to the *location and modality* of access. Because the connection was usable only at home, the intervention plausibly shifted time use toward the household, increasing awareness of service-delivery failures that motivate contact with local officials. The concentration of effects in complaints to ward and municipal officials—rather than in community meeting attendance—is consistent with a grievance-exposure channel operating through the home. The suggestive concentration of effects among men is consistent with this account, given baseline gender differences in time spent away from home. Notably, increased internet entertainment consumption among men coexists with their higher in-person participation, suggesting that the time-use channel dominates any entertainment substitution effect.

These preliminary findings underscore that the political consequences of "going online" depend not only on whether people have internet access, but on how they connect. Policies that expand home connectivity may strengthen local accountability and place-based participation even when they do not translate into higher turnout or online activism. Future work should examine how these effects evolve as home connections become more common, how they interact with local institutions and service delivery, and whether similar patterns emerge in other partially connected societies.

References

Aker, Jenny C. and Isaac M. Mbiti. 2010. "Mobile Phones and Economic Development in Africa." *Journal of Economic Perspectives* 24(3):207–232.

Boulianne, Shelley. 2009. "Does Internet Use Affect Engagement? A Meta-Analysis of Research." *Political Communication* 26(2):193–211.

Boulianne, Shelley. 2015. "Social Media Use and Participation: A Meta-Analysis of Current Research." *Information, Communication & Society* 18(5):524–538.

Campante, Filipe, Ruben Durante and Francesco Sobbrio. 2018. "Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation." *Journal of the European Economic Association* 16(4):1094–1136.

Choi, Donghyun Danny, Benjamin Laughlin and Kenneth A. Schultz. 2025. "Mobile Internet Technology and National Identity in Sub-Saharan Africa." Working paper.

Christensen, Darin and Francisco Garfias. 2018. "Can you hear me now? How communication technology affects protest and repression." *Quarterly journal of political science* 13(1):89–117.

Donati, Davide. 2023. "Mobile Internet Access and Political Outcomes: Evidence from South Africa." *Journal of Development Economics* 162:103073.

Enikolopov, Ruben, Alexey Makarin and Maria Petrova. 2020. "Social Media and Protest Participation: Evidence from Russia." *Econometrica* 88(4):1479–1514.

Falck, Oliver, Robert Gold and Stephan Heblich. 2014. "E-lections: Voting Behavior and the Internet." *American Economic Review* 104(7):2238–2265.

Farrell, Henry. 2012. "The Consequences of the Internet for Politics." *Annual Review of Political Science* 15(Volume 15, 2012):35–52.

Gavazza, Alessandro, Mattia Nardotto and Tommaso Valletti. 2019. "Internet and Politics: Evidence from UK Local Elections and Local Government Policies." *Review of Economic Studies* 86(5):2092–2135.

Ge, Shuning, Guy Grossman, Katrina Kosec, Apoorva Lal and Benjamin Laughlin. 2025. "The Effects of Cellphone Coverage Expansion on Wealth and Political Behavior." Working paper.

Hopkins, Daniel J. 2018. *The Increasingly United States: How and Why American Political Behavior Nationalized.* University of Chicago Press.

International Telecommunication Union. 2023. "Measuring Digital Development: Facts and Figures 2023.".

Manacorda, Marco and Andrea Tesei. 2020. "Liberation Technology: Mobile Phones and Political Mobilization in Africa." *Econometrica* 88(2):533–567.

Martin, Gregory J. and Joshua McCrain. 2019. "Local News and National Politics." *American Political Science Review* 113(2):372–384.

Olken, Benjamin A. 2009. "Do Television and Radio Destroy Social Capital? Evidence from Indonesian Villages." *American Economic Journal: Applied Economics* 1(4):1–33.

Prior, Markus. 2005. “News vs. Entertainment: How Increasing Media Choice Widens Gaps in Political Knowledge and Turnout.” *American Journal of Political Science* 49(3):577–592.

Reed, Matthew, Thecla Mbongue and Danson Njue. 2023. Africa Broadband Outlook 2023. Technical report Omdia.

Tucker, Joshua A., Andrew Guess, Pablo Barberá, Cristian Vaccari, Alexandra Siegel, Sergey Sanovich, Denis Stukal and Brendan Nyhan. 2018. “Social Media, Political Polarization, and Political Disinformation: A Review of the Scientific Literature.” *SSRN Electronic Journal* .

Zhuravskaya, Ekaterina, Maria Petrova and Ruben Enikolopov. 2020. “Political Effects of the Internet and Social Media.” *Annual Review of Economics* 12:415–438.

Appendix for *"Internet Access and Political Engagement: Evidence from South Africa"*

A Experimental Design

A.1 Pre-registration

Pre-analysis plans (PAPs) can be found at https://osf.io/4z7t2/overview and https://osf.io/cv5hk/overview.

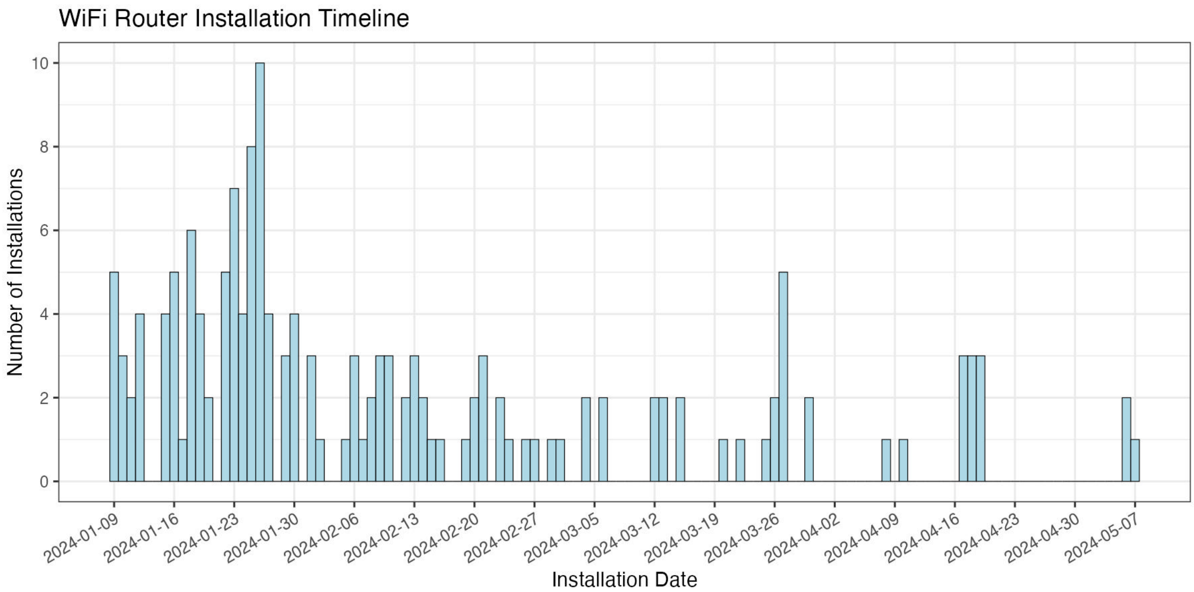
A.2 Installation and maintenance of the Wi-Fi routers

The Wi-Fi routers were installed between January 9th, 2024 and May 7th, 2024 (see Figure A.5). Project Isizwe made multiple concerted efforts to ensure that each household assigned to the Wi-Fi router treatment was reached via phone and in-person visits. These attempts were made to confirm that the household was still interested in receiving the router and to address any concerns or logistical issues. When a household member was successfully contacted and agreed to accept the Wi-Fi router, Project Isizwe coordinated a date for a technician to visit the household and install the necessary equipment. This included the installation of the Wi-Fi router and, where needed, a connector radio to amplify the signal and reach the closest hotspot.

During the installation, the technician detailed how to access the internet through the router, instructed on managing the connection, and provided contact information for further assistance. A printed document was distributed at the end of the visit to ensure the household would have a reference to recall details and support resources when needed.

After the installation, Project Isizwe provided ongoing technical support to address connectivity issues, troubleshoot any technical problems that household members might encounter, and ensure a seamless user experience. To facilitate efficient communication, the team created a WhatsApp group chat with the recipients, which enabled quick and easy access to support and assistance as needed. Importantly, household members were informed that the Wi-Fi router would remain in place but that Project Isizwe would dismantle and remove it upon request if they no longer wished to have the service.

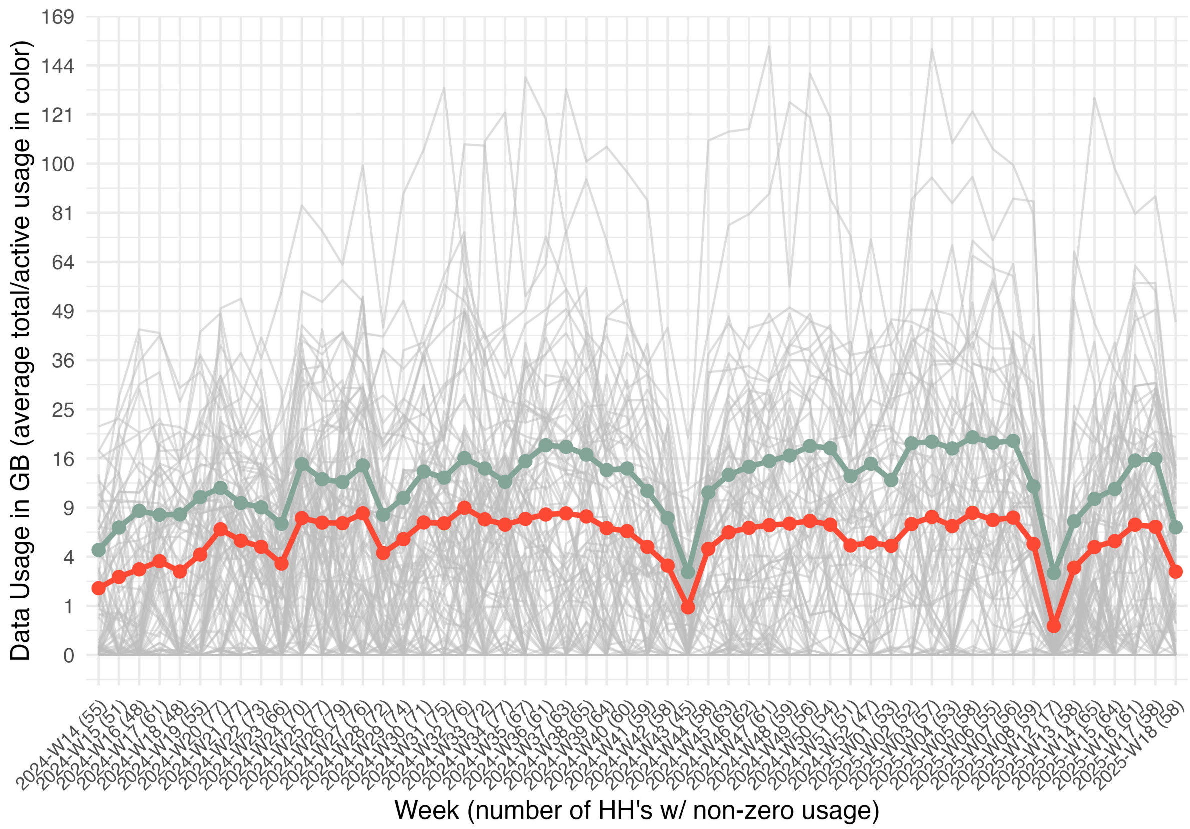
Figure A.5: Wi-Fi Router Installation Timeline



Note: The figure displays the number of Wi-Fi router installations completed between January 9 and May 7 2024. The horizontal axis indicates the installation date, and the vertical axis reports the count of installations on each date.

A.3 Internet utilization

Figure A.6: Average Daily Household Internet Utilization in GB across Study Weeks



Note: The figure displays household-level internet utilization in GB averaged per week over time for households assigned to treatment. Bold colored lines show average use in GB across all treatment households, and all households that utilized the internet via Wi-Fi router during the respective week.

A.4 Block randomization

For the Wi-Fi router intervention, we randomly assigned 200 out of our 400 study households to receive a home Wi-Fi router. We form matched pairs of similar households based on longitude and latitude, baseline measures of the primary respondent's political knowledge, gender, access to an internet-capable device, and political engagement in-person and online. Specifically, we constructed the following variables:

- `geopoint_1latitude` / `geopoint_1longitude`: Longitude and latitude recorded at the beginning
- `fb_political_index`: Index of respondent's political activity on Facebook
- `pol_activity_index`: Index of respondent's offline political activity
- `device_access`: Indicator of access to an internet-capable device
- `gender`: Indicator for respondent gender
- `knowledge_national`: Indicator for whether respondent could correctly name the current finance minister or mayor of their municipality

We used these covariates to form pairs because we deem it likely that these covariates are predictive of potential outcomes. For the coding of longitude and latitude, we used the raw longitude and latitude values recorded by enumerator tablets at the beginning of the baseline survey. We enforced that units in a pair had to be matched exactly on gender and `knowledge_national`. Our pre-analysis plan (https://osf.io/4z7t2/overview) documents the baseline survey items used to construct these covariates, along with the code used to generate the indices and implement the block randomization. Matched pairs were created using `blockTools::block`, after which we randomly assigned one unit in each pair to treatment using `randomizr::block_ra`.

A.5 GOTV Campaign

Social media campaigns play a pervasive role in the politics of industrialized countries. The same begins to be true in developing countries as internet access expands throughout the developing world. To better understand how internet scarcity shapes the effects of such a campaign, we designed an online Get-Out-The-Vote (GOTV) campaign in collaboration with Sthembiso Mngoma, a Durban-based Facebook influencer (facebook.com/StheMngoma.ZA). The campaign's goal was to encourage Durban residents to turn out to vote in the 2024 national elections on May 29th, 2024.

The campaign took the following form: On April 27th, 2024, Sthembiso posted an initial Facebook announcement that encouraged his followers to share a short (up to 30 seconds) video explaining why voting in the upcoming election is important. The post explained that, across the next four weeks up until the election, Sthembiso would post five of the submitted videos every week. The most popular video of the five would win a cash prize of R1000 (around $54). Right before the election, one of the four weekly winners would be selected as a winner of the overall competition. The overall winner would receive a grand prize in the form of an iPhone 14. The competition ran for four weeks until May 24th, 2024. In the final week, Sthembiso posted the four weekly winners and announced the final contest between them. The announcement of the final winner was posted on May 30th, 2024, right after the national elections in South Africa.

Our cross-cutting GOTV campaign treatment encourages our study participants to participate or engage with the GOTV campaign. Throughout the four weeks of the campaign, we sent a series of text messages to the phone numbers of 200 randomly assigned study participants. These messages promoted the GOTV campaign and included a link to Sthembiso's Facebook page. We used the service Zoomconnect (zoomconnect.com/) to send the messages in bulk and tracked which study participants received the messages using the delivery status updates provided by the platform.

We randomly assigned 200 out of our 400 study households to the GOTV campaign. We used the assignment status for the Wi-Fi router treatment as a block indicator and randomly assigned 100 out of 200 households in, respectively, the Wi-Fi router treatment and control group to the GOTV campaign encouragement treatment. The resulting intervention design was fully factorial, with 100 households assigned to each of the following conditions:

- No Wi-Fi router, No GOTV campaign encouragement
- Wi-Fi router, No GOTV campaign encouragement
- No Wi-Fi router, GOTV campaign encouragement
- Wi-Fi router, GOTV campaign encouragement

In each household assigned to the campaign, only the main respondent sampled at baseline received the text message encouragement, i.e., we really conducted this experiment on our sample of $N = 400$ baseline respondents, one in each of the study households.

In this paper, we marginalize across this treatment and compare respondents from all households assigned to the Wi-Fi router treatment to all respondents from households not assigned to the Wi-Fi router treatment, irrespective of whether a household was assigned to the GOTV campaign. Note that the same share of households in both groups received the GOTV campaign.

A.6 Attrition

We assessed whether rates and patterns of attrition were related to treatment. Our main concern was attrition induced by the Wi-Fi treatment, since respondents were asked at baseline whether they were interested in receiving a Wi-Fi router. To the degree that respondents in the treatment group associated the baseline survey with the router intervention, they may have been more willing to participate in follow-up data collection.

We conducted three primary tests:

(1) **Household structure / second-respondent eligibility.** We tested whether assignment to the Wi-Fi router treatment predicted whether enumerators reported that a household was a single-member household (i.e., no second adult permanently residing in the household who fulfilled the eligibility criteria). We created a household-level indicator for being reported as a single-member household and regressed this indicator on an indicator for assignment to the Wi-Fi treatment. We used randomization inference (RI) to conduct a two-tailed test of the sharp null hypothesis of no effect. *Resulting RI p-value is 0.2982.*

(2) **Differential attrition by Wi-Fi assignment.** We regressed an indicator for whether a respondent attrited on an indicator for assignment to the Wi-Fi treatment and tested the sharp null hypothesis of no effect using RI. *Resulting RI p-value is 0.1175.*

(3) **Differential attrition patterns (treatment-by-covariate interactions).** We regressed the same attrition indicator on the Wi-Fi treatment indicator, the baseline covariates listed below, and the complete set of treatment-by-covariate interactions. We used RI to conduct an F-test of the null hypothesis that all treatment-by-covariate interaction terms were zero. *Resulting RI F-test p-value is 0.6896.*

We ran the interaction test using the following baseline covariates, which included both covariates used for precision adjustment in the main specification and covariates used for subgroup analyses[12]:

- `part_inperson_bl`
- `part_online_bl`
- `knowledge_officials_bl`
- `device_access_bl`

[12] See details on construction of indices of in-person political participation, online political participation, and political knowledge in Appendix A.7.1.

- `vote_2019_clean_bl`
- `whatsapp_group_bl`
- `news_social_media_bl`
- `female_bl_el`

Since none of the primary attrition tests rejected at the 5% level (i.e., all relevant tests yielded $p \geq 0.05$), we rely on naive estimates based on the interviewed sample when analyzing the Wi-Fi treatment.

A.7 Details on the regression specification

A.7.1 Covariates

The vector of covariates $\mathbf{x}_j$ in our model consists of four pre-specified covariates measured during our baseline survey. Because only one respondent was interviewed at baseline, measures from the baseline survey are treated as household-level measures for endline analyses, i.e., all second respondents receive the same baseline values on a given measure as the baseline respondent in their household. This is the case for all covariates, including the moderators that we use for analyses that involve sub-group effects and differences between them. The exception is our measure of gender, which we use only for subgroup analyses. Since respondents' gender is unlikely to be affected by treatment, we rely on baseline measures of respondent gender for respondent 1 but endline measures of respondent gender for respondent 2 in each household. The covariates in our pre-registered main specification are:

- in-person political participation
- online political participation
- political knowledge
- access to an internet-capable device

We control for these covariates because they are likely to predict potential outcomes. Although we used similar covariates when forming blocks, the indices for in-person political participation, online political participation, and political knowledge used for blocking were constructed from a more limited set of items. We now rely on the extended indices, which draw on a larger share of our data and better capture the underlying constructs. While we blocked on latitude and longitude, we omit these variables here because we do not expect geographic location to predict potential outcomes. We also blocked on the gender of respondent 1, but exclude this covariate from the adjustment set because the endline sample includes one man and one woman per household when available. Below, we describe these covariates in detail including the question wording and how the indices are constructed.

In-person political participation: To create an index that captures respondents' in-person political participation, we used the following six questions included in the baseline survey:

(1) `attend_meeting_councilor_bl`. Now I would like you to think about the time since last Christmas. Have you done any of the following? Since last christmas, have you: Attended a community meeting with your Ward councilor

(2) `attend_meeting_party_bl`. Now I would like you to think about the time since last Christmas. Have you done any of the following? Since last christmas, have you: Attended a community meeting held by a political party

(3) `attend_meeting_community_bl`. Now I would like you to think about the time since last Christmas. Have you done any of the following? Since last christmas, have you: Attended another kind of community meeting

(4) `complain_ward_inperson_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to the Ward Councilor or Ward Officials? If yes: How did you contact the ward councilor or Ward officials?

(5) `complain_municipality_inperson_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to the Municipality Officials (including the mayor)? If yes: How did you contact municipality officials (including the mayor)?

(6) `complain_party_inperson_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to a local political party branch? If yes: How did you contact a local political party branch?

For the first three questions, each item was coded as a binary indicator equal to 1 if the respondent answered yes and 0 if the respondent answered no. The remaining three questions were also coded as binary indicators, taking the value 1 if the respondent reported yes and (&) indicated that the contact occurred in-person, and zero if the respondent answered no or (|) reported contact that did not occur in-person. We classify contact as in-person if the respondent selected any of the following options: went to the office in-person, called the office, asked another person to contact the office on their behalf, or selected other and specified a method that did not involve the internet.

The in-person political participation index was then constructed as the average of these six indicators for each respondent. The index therefore represents the share of activities in which the respondent reported participation, with higher values indicating greater local in-person political participation.

Online political participation: To measure respondents online political participation, we constructed an index using the following six questions from the baseline survey:

(1) `complain_ward_online_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to the Ward Councilor or Ward Officials? If yes: How did you contact the ward councilor or Ward officials?

(2) `complain_municipality_online_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to the Municipality Officials (including the mayor)? If yes: How did you contact municipality officials (including the mayor)?

(3) `complain_party_online_bl`. Now I would like you to think about the time since last Christmas. Have you ever contacted any of the following organizations to complain about an issue? Have you complained to a local political party branch? If yes: How did you contact a local political party branch?

(4) `ward_facebook_bl`. Have you ever visited your Ward's Facebook page? [If visited Ward's Facebook page:] Do you follow your Ward's Facebook page? [If visited Ward's Facebook page:] Have you ever reacted to a post or posted on your Ward's Facebook page?

(5) `municipality_facebook_bl`. Have you ever visited the Facebook page of eThekwini municipality? [If visited Facebook page:] Do you follow the Facebook page of eThekwini municipality? [If visited Facebook page:] Have you ever reacted to a post or posted on the Facebook page of eThekwini municipality?

(6) `party_facebook_bl`. Have you ever visited the Facebook page of a political party? [If visited Facebook page:] Do you follow the Facebook page of a political party? [If visited Facebook page:] Have you ever reacted to a post or posted on the Facebook page of a political party?

The first three questions were coded as binary indicators equal to 1 if the respondent answered yes and (&) reported contacting the relevant office online, and 0 if the respondent answered no or (|) reported contact that did not occur online. We classify contact as online if the respondent selected any of the following options: sent an email, used a contact form on a website, contacted the office on Facebook including tagging them in a post, sent a WhatsApp message, or selected other and specified a method that involved the internet.

For the remaining three questions, responses were coded on a three-point scale. We assigned a value of 0 if the respondent had not visited the Facebook page, 0.5 if the respondent had visited the page but did not follow it and had not reacted or posted, and 1 if the respondent followed the page or (|) had reacted to or posted content on it.

The online political participation index was then constructed as the average of these six items for each respondent, with higher values indicating greater levels of online political participation.

Political knowledge: In the baseline survey, respondents were asked whether they knew the name of the Ward Councilor of their community and, if so, were asked to state the name. The same set of questions was also asked about the current Mayor and the Minister of Finance.

(1) `know_councilor_bl`. Do you know the name of the Ward Councilor responsible for your community? If yes: Please tell me the name of the ward Councilor responsible for your community.

(2) `know_mayor_bl`. Do you know the name of the Mayor of your municipality? If yes: Please tell me the name of the mayor of your municipality.

(3) `know_minister_bl`. Do you know the name of the current Minister of Finance? If yes: Please tell me the name of the current Minister of Finance.

Each item was coded as 1 if the respondent answered yes and (&) provided a correct answer, and 0 if the respondent answered yes but provided an incorrect answer or (|) answered no. Following the approach used for the other indices, we constructed an index of political knowledge by taking the average of these three indicators, with higher values indicating greater political knowledge.

Access to an internet-capable device: Finally, the baseline survey asked respondents whether they had access to an internet-capable device:

(1) `device_access_bl`. Do you own a device that can connect to the internet (like a smartphone, tablet or computer)?

We constructed a binary variable that takes the value 1 if the respondent reported access to an internet-capable device and 0 otherwise.

A.7.2 Estimation of heterogeneous effects

To estimate sub-group effects and differences between them, we use the same specifications but include an indicator m_j for sub-group membership of respondent i in household j and the interaction between this indicator and the treatment assignment indicator:

$$y_{ij} = \alpha + \tau_c z_j + \gamma m_j + \tau_{\text{diff}} z_j \times m_j + \beta^T x_j + \epsilon_{ij}$$

If the mediator m_j (or any constituent item of m_j, if m_j is an index) is also included in the vector x_j of covariates, we omit m_j (or the respective constituent item of m_j) from x_j.

A.8 Descriptive statistics

Variable	Obs	Mean	SD	Min	p25	p50	p75	Max
Endline survey (Total $N = 800$)								
Female	558	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Age	562	30.86	9.83	18.00	24.00	29.00	35.00	65.00
Ethnic group: Zulu	562	0.76	0.43	0.00	1.00	1.00	1.00	1.00
Baseline survey (Total $N = 400$)								
Internet connection: Home	400	0.15	0.36	0.00	0.00	0.00	0.00	1.00
Internet connection: Mobile	400	0.85	0.36	0.00	1.00	1.00	1.00	1.00
Internet connection: Public	400	0.18	0.38	0.00	0.00	0.00	0.00	1.00
Has access to cellphone	400	0.85	0.36	0.00	1.00	1.00	1.00	1.00
In-person participation (index)	400	0.19	0.22	0.00	0.00	0.17	0.33	1.00
Online participation (index)	400	0.12	0.14	0.00	0.00	0.08	0.17	0.67
Know officials (index)	400	0.30	0.27	0.00	0.00	0.33	0.33	1.00
HH size	400	5.39	3.56	1.00	3.00	5.00	7.00	25.00
HH assets (index)	399	0.58	0.22	0.11	0.44	0.56	0.78	1.00
HH assets: TV	399	0.84	0.36	0.00	1.00	1.00	1.00	1.00
HH assets: Computer	399	0.27	0.44	0.00	0.00	0.00	1.00	1.00

B Mechanism Analysis

B.1 Outcome measurement

To capture respondents' partisan preferences, we rely on survey items measuring support for established political parties, including the ANC or the DA (`party_anc_da`), or support for newer political parties such as MK (`party_mk`). We also measure the strength of respondents' partisan identity (`strength_partisan_identity`) using a separate item that captures how strongly they identify with their preferred party.

- `party_anc_da`. "Do you feel close to any particular political party? [If yes] Which party is that?" 1 = respondent says they feel close to political party and choose African National Congress (ANC) OR Democratic Alliance (DA) in the follow up question, 0 = respondent says they do not feel close to any political party or that they do, but choose a party other than the African National Congress (ANC) or Democratic Alliance (DA) in the follow up question.
- `party_mk`. "Do you feel close to any particular political party? [If yes] Which party is that?" 1 = respondent says they feel close to political party and choose uMkhonto weSizwe Party (MK) in the follow up question, 0 = respondent says they do not feel close to any political party or that they do, but choose party other than uMkhonto weSizwe Party (MK) in the follow up question.
- `strength_partisan_identity`. "Do you feel close to any particular political party? [If yes] Do you feel very close to [plug-in choice from the previous question] or just a little close?" 0 = No, 0.5 = Yes AND just a little close, 1 = Yes AND very close.

To capture political evaluation and efficacy, we use survey questions measuring government approval and political self-efficacy. Government approval (`gov_approval`) is measured using an index constructed by averaging three items that assess respondents' satisfaction with the government, their Ward, and the president. Political self-efficacy is measured using a standalone item in which respondents are asked to select the statement that comes closer to their own view (`efficacy`).

- `gov_approval`.
  (1) `satisfaction_government`. "Which of the following statements do you agree with more?" 1 = Some government officials in South Africa are doing a good job. 0 = Almost all government officials in South Africa are too corrupt to do a good job.
  (2) `satisfaction_ward`. "Please tell me, how satisfied are you with the performance of your Ward councilor?" 1= Very satisfied, 0.66 = Somewhat satisfied, 0.33 = Somewhat dissatisfied, 0 = Very dissatisfied.
  (3) `satisfaction_president`. "And finally, what about the president of South Africa? How satisfied are you with the president's performance?" 1= Very satisfied, 0.66 = Somewhat satisfied, 0.33 = Somewhat dissatisfied, 0 = Very dissatisfied.
- `efficacy`. "Which of the following two statements comes closest to your view?" 0 = It is difficult for people like me to solve countrywide problems, such as the shortage of jobs or problems with service delivery. 1 = People like me can solve such problems if we make our voices heard.

To assess respondents' voting attitudes and behaviors, we use three variables: voting norms (`voting_norms`), voting attitudes (`voting_attitudes`), and prior voter registration (`registered_prior`).

The first two outcomes are indices constructed by averaging their constituent items. Prior voter registration is measured using a single item asking whether the respondent was registered to vote before the 2024 national election.

- `voting_norms.`
  (1) `voting_norms1.` "Next, I would like to learn about the views of most other people in your community. Please tell me which of the following statements comes closest to your view." 1 = Most people in my community believe strongly that one should turn out to vote. 0 = Most people in my community do not care much about whether one turns out to vote.
  (2) `voting_norms2.` "Finally, imagine your neighbor did not vote in a national election, and other members of your community found out about that. Which of the following scenarios do you believe to be most likely?" 1 = The other members of my community would judge my neighbor for not voting. 0.5 = The other members of my community would not care about my neighbor not voting. 0 = The other members of my community would agree with my neighbor's decision to not vote.
- `voting_attitudes.`
  (1) `voting_effectiveness.` "Please tell me which statement you agree more with, even if you do not agree fully with either statement." 1 = Voting will get you what you want as a citizen. 0 = Voting is not the most effective way to get you what you want as a citizen.
  (2) `voting_duty.` "And what about the following two statements? Which do you agree with more?" 1 = As citizens, it is our duty to make our voices heard by turning out to vote. 0 = Voting is a right but it is not a duty for us citizens.
- `registered_prior.` "People sometimes do not vote in elections, for example, because they are not registered, cannot go to their polling station, or someone prevents them from doing so. What about you? Did you vote in the last national elections on May 29, 2024? [If No:] Were you registered to vote before the last national elections on May 29, 2024?" 1 if voted OR not voted but registered, 0 if not registered.

To capture respondents' political knowledge, we created three indices: knowledge of political parties (`knowledge_parties`), knowledge of voting procedures (`knowledge_voting`), and knowledge of public officials (`knowledge_officials`). For the first two indices, respondents are presented with a series of statements and asked to indicate whether each statement is true or false. Each item is coded as 1 if the respondent correctly identifies the information and 0 if the response is incorrect or if the respondent indicates that they do not know the answer. The third index consists of questions asking whether respondents know their officials and, if so, to name them. Each item is coded as 1 if the respondent answers Yes and provides the correct name, and 0 if the respondent answers Yes but provides an incorrect name or answers No. Each index is constructed by averaging its constituent items.

- `knowledge_parties.`
  (1) `party_knowledge_nhi_mk.` "The MK Party advocates implementing NHI to redistribute resources away from expensive private healthcare systems." [Correct answer: TRUE]
  (2) `party_knowledge_nhi_anc.` "The ANC is against NHI, advocating introducing social reinsurance for medical schemes - a public programme to transfer risks that individual insurers find difficult to cover." [Correct answer: FALSE]

(3) party_knowledge_borders_mk. "The MK Party advocates for reducing border security in favor of more open trade with neighboring countries." [Correct answer: FALSE]

(4) party_knowledge_sihle_mk. "Sihle Zikalala ran for the MK Party in the last national elections on May 29, 2024." [Correct answer: FALSE]

- knowledge_voting.

  (1) voting_knowledge_independents. "In the last national elections on May 29, 2024, independent candidates were allowed to contest elections for the first time." [Correct answer: TRUE]

  (2) voting_knowledge_ballots. "In the last national elections on May 29, 2024, voters received two ballots, one for the election of the National Assembly election and one for the election of the provincial legislature." [Correct answer: FALSE]

  (3) voting_knowledge_registration. "You can register to vote on election day." [Correct answer: FALSE]

  (4) voting_knowledge_online. "It is possible to check your voter registration status and your polling station online." [Correct answer: TRUE]

- knowledge_officials.

  (1) know_councilor. Do you know the name of the Ward Councilor responsible for your community? If yes: Please tell me the name of the ward Councilor responsible for your community.

  (2) know_mayor. Do you know the name of the Mayor of your municipality? If yes: Please tell me the name of the mayor of your municipality.

  (3) know_minister. Do you know the name of the current Minister of finance? If yes: Please tell me the name of the current minister of finance.

To assess respondents' media exposure, we focus on three domains. The first is news exposure, which captures whether respondents encountered recent news events (news_aware) or misinformation (misinformation_aware). For each question, respondents were asked whether they had heard about the issue or event prior to the survey. Responses are coded as 1 if the respondent indicates having heard about the item and 0 otherwise. Each index is created by averaging constituent items.

- news_aware.

  (1) news_aware_president_cyril. "During annual January 8th Statement at Mandela Park Stadium in Khayelitsha, President Cyril Ramaphosa said that ANC faces an existential crisis."

  (2) news_aware_mandela_gson. "Several people, including Nelson Mandela's grandson, were arrested at Mandela's former home in Houghton for possession of a hijacked vehicle."

  (3) news_aware_prime_minister_kzn. "King Misuzulu kaZwelithini has fired his prime minister, Thulasizwe Buthelezi."

  (4) news_aware_fire_kzn. "Fire destroyed 42 homes and left 83 homeless in informal settlement in Durban on New Year's Eve."

- misinformation_aware.

(1) misinformation_aware_courier. "Couriers are being recruited nationwide to kidnap children for R120,000."

(2) misinformation_aware_spar_work. "Spar South Africa offered part-time work through Facebook in December."

(3) misinformation_aware_sassa. "The South African Social Security Agency (SASSA) is offering a R500 grant to people over 70 who suffer from chronic illnesses."

The second is information accuracy, measured through respondents' ability to correctly identify factual news (news_correct) and misinformation (misinformation_correct). Enumerators began by telling respondents, "I will read you some statements about recent events. Some of these statements are true, and others are false. Please tell me for each statement whether you think it is true or false." Responses are coded as 1 if the respondent provides the correct answer and 0 if the response is incorrect or if the respondent indicates that they do not know. Each index is created by averaging constituent items.

- news_correct.
  (1) news_correct_president_cyril. "During annual January 8th Statement at Mandela Park Stadium in Khayelitsha, President Cyril Ramaphosa said that ANC faces an existential crisis." [Correct answer: TRUE]
  (2) news_correct_mandela_gson. "Several people, including Nelson Mandela's grandson, were arrested at Mandela's former home in Houghton for possession of a hijacked vehicle." [Correct answer: TRUE]
  (3) news_correct_prime_minister_kzn. "King Misuzulu kaZwelithini has fired his prime minister, Thulasizwe Buthelezi." [Correct answer: TRUE]
  (4) news_correct_fire_kzn. "Fire destroyed 42 homes and left 83 homeless in informal settlement in Durban on New Year's Eve." [Correct answer: TRUE]
- misinformation_correct.
  (1) misinformation_correct_courier. "Couriers are being recruited nationwide to kidnap children for R120,000." [Correct answer: FALSE]
  (2) misinformation_correct_spar_work "Spar South Africa offered part-time work through Facebook in December." [Correct answer: FALSE]
  (3) misinformation_correct_sassa. "The South African Social Security Agency (SASSA) is offering a R500 grant to people over 70 who suffer from chronic illnesses." [Correct answer: FALSE]

The third concerns media trust, assessed through trust in traditional media (trust_offline) and trust in social media or messaging platforms (trust_social_media). Each index is created by averaging constituent items.

- trust_offline. Enumerators began by telling respondents, "Next, we would like to know how much you trust information about current events you learn from various sources. For each of the following sources, tell us whether you trust the information from them a great deal, trust quite a lot, do not trust a lot, or do not trust at all." Responses are coded as: 1 = Trust a great deal, 0.667 = Trust quite a lot, 0.334 = Do not trust a lot, 0 = Do not trust at all.
  (1) trust_tv. "Television"

(2) `trust_radio.` “Radio"

- `trust_social_media.` Enumerators began by telling respondents, “Next, we would like to know how much you trust information from the following sources. We are interested in your views on the trustworthiness of these sources even if you don’t usually get news from them. For each of the following sources, tell us whether you trust the information from them a great deal, trust quite a lot, do not trust a lot, or do not trust at all." Responses are coded as: 1 = Trust a great deal, 0.667 = Trust quite a lot, 0.334 = Do not trust a lot, 0 = Do not trust at all.

  (1) `trust_fb.` “Facebook"

  (2) `trust_whatsapp.` “WhatsApp"

B.2 Additional results

Table B.5: News Consumption and Misinformation Exposure

	Social media time	WhatsApp usage (tracked)	News via family/friends	WhatsApp preload	News via social media	News via large groups	News frequency	Internet for news	Traditional media	In-person news	Follow MK on FB	MK knowledge
WiFi	0.018	0.084	0.004	0.011	-0.026	-0.067*	0.026	-0.008	0.021	0.059*	0.000	0.023
	[0.136]	[0.417]	[0.037]	[0.042]	[0.033]	[0.038]	[0.023]	[0.032]	[0.032]	[0.030]	[0.023]	[0.022]
Outcome range	log(1 + hours)	log(1 + hours)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)
Control SD	1.622	2.424	0.447	0.487	0.390	0.451	0.275	0.382	0.365	0.360	0.281	0.279
Control mean	3.854	4.958	0.593	0.382	0.735	0.467	0.636	0.620	0.702	0.731	0.086	0.516
Hypotheses	two	two	two	two	two	two	two	two	two	two	two	two
Observations	562	137	562	558	562	562	562	562	562	562	535	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Social media time* is self-reported time spent on WhatsApp, Facebook, YouTube, and TikTok. *WhatsApp usage (tracked)* is the average log-transformed time since last WhatsApp activity, measured via metadata tracking. *News via family/friends* captures learning news via social media from family or friends. *WhatsApp preload* indicates automatic downloading of media on WhatsApp. *News via social media* captures learning news via social media platforms. *News via large groups* captures learning news via large social media groups or influencers. *News frequency* measures how frequently the respondent follows local or national news. *Internet for news* indicates using the internet to learn about events. *Traditional media* captures learning news via TV and radio. *In-person news* captures learning news through in-person interactions. *Follow MK on FB* indicates following the MK party on Facebook. *MK knowledge* is an index of knowledge about MK party platforms and candidates.

Table B.6: Effect of home Wi-Fi on news consumption and misinformation

	News via large groups	Exposed to misinformation	News via social media	Trust in social media/messengers	Correctly identifies misinformation	Knows recent events	News via traditional media	News frequency	Correctly identifies news	Trust in traditional media	In-person news
WiFi	-0.067*	-0.049*	-0.026	-0.004	0.012	0.014	0.021	0.026	0.034	0.044**	0.059*
	[0.038]	[0.025]	[0.033]	[0.024]	[0.027]	[0.026]	[0.032]	[0.023]	[0.026]	[0.019]	[0.030]
Outcome range	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Control SD	0.451	0.293	0.390	0.289	0.305	0.286	0.365	0.275	0.290	0.233	0.360
Control mean	0.467	0.426	0.735	0.421	0.389	0.378	0.702	0.636	0.400	0.795	0.731
Hypotheses	two	two	two	two	two	two	two	two	two	two	two
Observations	562	562	562	562	562	562	562	562	562	562	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *News via large groups* is an index of learning news via large WhatsApp groups or influencer channels on social media. *Exposed to misinformation* is an index of whether the respondent reports having heard three fabricated news stories. *News via social media* is an index of learning news via social media platforms. *Trust in social media/messengers* is an index of reported trust in Facebook and WhatsApp as sources of information. *Correctly identifies misinformation* is an index of whether the respondent correctly identifies the three fabricated stories as false. *Knows recent events* is an index of whether the respondent reports having heard about four recent real news events. *News via traditional media* is an index of learning news via TV, radio, or newspapers. *News frequency* is an index of how frequently the respondent follows local and national news. *Correctly identifies news* is an index of whether the respondent correctly identifies the four real news stories as true. *Trust in traditional media* is an index of reported trust in TV and radio as sources of information. *In-person news* is an index of learning news through in-person conversations or community meetings.

Table B.7: Effect of home Wi-Fi on political views and knowledge

	Registered to vote	Support ANC or DA	Voting norms	Self-efficacy	Knows officials	Knows about parties	Knows voting rules	Support MK	Voting attitudes	Strong partisan	Government approval
WiFi	-0.054	-0.028	-0.017	-0.013	-0.004	0.005	0.013	0.017	0.016	0.019	0.033
	[0.040]	[0.029]	[0.026]	[0.040]	[0.018]	[0.020]	[0.020]	[0.041]	[0.033]	[0.037]	[0.024]
Outcome range	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Control SD	0.451	0.349	0.294	0.499	0.218	0.253	0.234	0.471	0.369	0.431	0.277
Control mean	0.719	0.141	0.571	0.539	0.267	0.507	0.583	0.331	0.450	0.407	0.272
Hypotheses	two	two	two	two	two	two	two	two	two	two	two
Observations	561	558	562	560	562	562	562	558	562	558	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Registered to vote* indicates whether the respondent was registered to vote before the 2024 election. *Support ANC or DA* indicates feeling close to the ANC or DA. *Voting norms* is an index of perceived community norms about voter turnout. *Self-efficacy* captures whether the respondent believes ordinary people can solve countrywide problems. *Knows officials* is an index of correctly naming the ward councilor, mayor, and minister of finance. *Knows about parties* is an index of knowledge about MK and ANC party platforms. *Knows voting rules* is an index of knowledge about the voting process. *Support MK* indicates feeling close to the MK party. *Voting attitudes* is an index of beliefs about voting effectiveness and civic duty. *Strong partisan* captures the strength of partisan identity. *Government approval* is an index of satisfaction with government, ward councilor, and president performance.

Table B.8: Effect of home Wi-Fi on time use

	Socializing	Paid work	Time with family	Unpaid care	Domestic work	Job search	Personal care	Social media	Internet enter-tain-ment	Personal leisure	Education	Video enter-tain-ment	Using Internet	Time spent at home
WiFi	-0.115*	-0.018	-0.018	-0.012	0.007	0.005	0.004	0.014	0.057*	0.066	0.067	0.082	0.104*	0.351
	[0.066]	[0.080]	[0.030]	[0.050]	[0.058]	[0.018]	[0.042]	[0.034]	[0.030]	[0.060]	[0.042]	[0.061]	[0.059]	[0.238]
Outcome range	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)
Control SD	0.777	0.919	0.374	0.620	0.725	0.187	0.514	0.431	0.291	0.718	0.448	0.694	0.696	2.753
Control mean	0.745	0.557	0.135	0.362	1.085	0.034	1.518	0.152	0.094	1.397	0.138	0.781	0.591	6.675
Hypotheses	two	two	two	two	two	two	two	two	two	two	two	two	two	two
Observations	561	561	561	561	561	561	561	561	561	561	561	561	561	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). All outcomes are log-transformed total minutes spent on each activity, measured via a time use survey. *Time spent at home* is the total time spent at home across all activities. *Using Internet* is the total time spent using the internet. *Social media* and *Internet entertainment* capture time on social media apps and online entertainment, respectively. *Video entertainment* captures time watching TV or videos. *Time with family* captures time spent with family members at home.

Table B.9: Effect of home Wi-Fi on time use by gender

	Socializing	Paid work	Time with family	Unpaid care	Domestic work	Job search	Personal care	Social media	Internet entertainment	Personal leisure	Education	Video entertainment	Using Internet	Time spent at home
WiFi	-0.089	0.018	-0.031	-0.065	0.009	-0.011	0.109*	-0.025	0.113**	-0.007	0.074	0.088	0.067	0.391
	[0.099]	[0.126]	[0.044]	[0.048]	[0.085]	[0.030]	[0.060]	[0.052]	[0.048]	[0.093]	[0.060]	[0.091]	[0.090]	[0.338]
Woman	-0.225**	-0.337***	-0.023	0.405***	0.535***	-0.054**	0.055	-0.033	0.014	-0.133	0.065	0.002	0.004	1.610***
	[0.095]	[0.122]	[0.046]	[0.067]	[0.079]	[0.024]	[0.062]	[0.056]	[0.035]	[0.090]	[0.053]	[0.085]	[0.085]	[0.323]
WiFi x Woman	-0.027	-0.056	0.024	0.094	-0.009	0.032	-0.209**	0.074	-0.105*	0.121	-0.013	-0.032	0.060	-0.196
	[0.129]	[0.158]	[0.060]	[0.092]	[0.113]	[0.035]	[0.083]	[0.074]	[0.058]	[0.129]	[0.084]	[0.125]	[0.120]	[0.441]
Outcome range	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)	log(1 + min)
Control SD	0.777	0.919	0.374	0.620	0.725	0.187	0.514	0.431	0.291	0.718	0.448	0.694	0.696	2.753
Control mean	0.745	0.557	0.135	0.362	1.085	0.034	1.518	0.152	0.094	1.397	0.138	0.781	0.591	6.675
Hypotheses	two	two	two	two	two	two	two	two	two	two	two	two	two	two
Observations	557	557	557	557	557	557	557	557	557	557	557	557	557	558

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on parametric standard errors. All outcomes are log-transformed total minutes spent on each activity, measured via a time use survey. Each column reports the treatment effect for the full sample (WiFi), the interaction with a female indicator (WiFi $\times$ Female), and the treatment effect among men (WiFi | Male) and women (WiFi | Female) separately.

Table B.10: Effect of home Wi-Fi on news and misinformation

	Exposed to misinformation	Trust in social media/messengers	Correctly identifies misinformation	Exposed to news events	Correctly identifies news	Trust in traditional media
WiFi	-0.049*	-0.004	0.012	0.014	0.034	0.044**
	[0.025]	[0.024]	[0.027]	[0.026]	[0.026]	[0.019]
Outcome range	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Control SD	0.293	0.289	0.305	0.286	0.290	0.233
Control mean	0.426	0.421	0.389	0.378	0.400	0.795
Hypotheses	two	two	two	two	two	two
Observations	562	562	562	562	562	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Exposed to misinformation* is an index of whether the respondent reports having heard three fabricated news stories. *Trust in social media/messengers* is an index of reported trust in Facebook and WhatsApp as sources of information. *Correctly identifies misinformation* is an index of whether the respondent correctly identifies the three fabricated stories as false. *Exposed to news events* is an index of whether the respondent reports having heard about four recent real news events. *Correctly identifies news* is an index of whether the respondent correctly identifies the four real news stories as true. *Trust in traditional media* is an index of reported trust in TV and radio as sources of information.

Table B.11 disaggregates the in-person political participation index into its six constituent binary items: attending a councilor meeting, attending a party meeting, attending a community meeting, and complaining in-person to ward officials, the municipality, or a political party. Each outcome equals 1 if the respondent reports engaging in the activity in the past 12 months and 0 otherwise. The table shows that the positive treatment effect on the aggregate index is not driven by a single item but reflects increases across multiple forms of in-person engagement, particularly attendance at community meetings and complaints to ward and municipal officials.

Table B.11: Disaggregated in-person political participation items

	In-person participation					
	Attend councilor meeting	Attend party meeting	Attend community meeting	Complain to ward (in-person)	Complain to municipality (in-person)	Complain to party (in-person)
WiFi	0.054	0.034	0.049	0.062	0.067**	-0.011
	[0.036]	[0.036]	[0.040]	[0.043]	[0.029]	[0.027]
Outcome range	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Control SD	0.424	0.439	0.471	0.465	0.290	0.349
Control mean	0.233	0.259	0.330	0.315	0.093	0.141
Hypotheses	two	two	two	two	two	two
Observations	562	562	562	562	561	561

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). This table disaggregates the *In-person participation* index into its six constituent binary items. Each outcome equals 1 if the respondent reports engaging in the activity in the past 12 months and 0 otherwise.

C Complier Average Causal Effects

The main-text tables report intent-to-treat (ITT) estimates based on random assignment to the Wi-Fi router treatment. Because not all households assigned to treatment received a functioning router, we also report complier average causal effects (CACE) estimated via two-stage least squares (2SLS). In the first stage, we instrument actual Wi-Fi installation with random treatment assignment; the first-stage coefficient is approximately 0.78, indicating that 78% of households assigned to the treatment group received a working router. The resulting CACE estimates are larger in magnitude than the corresponding ITT estimates by a factor of roughly $1/0.78 \approx 1.28$, and the pattern of statistical significance is preserved across all outcomes.

C.1 Political participation

Table C.12: CACE: Effect of home Wi-Fi access on political participation

	In-person participation	Has voted in 2024	Online participation
Received WiFi	0.048**	-0.074	-0.015
	[0.023]	[0.049]	[0.013]
Outcome range	[0,1]	[0,1]	[0,1]
Control SD	0.250	0.496	0.163
Control mean	0.228	0.570	0.139
First-stage coef.	0.881	0.881	0.881
Hypotheses	two	two	upr
Observations	562	562	562

Signif. Codes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Note: Estimates are complier average causal effects (CACE) obtained via two-stage least squares (2SLS), instrumenting actual Wi-Fi installation with random Wi-Fi assignment. CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *In-person participation* is an index capturing whether respondents attended community, Ward, or party meetings in the past 12 months and whether they contacted these actors in person to raise an issue. *Has voted in 2024* indicates whether the respondent reports voting in the 2024 national election; results are the same when using the thumb print verified measure available for part of the sample. *Online participation* is an index measuring whether respondents complained to the Ward, municipality, or party online and how much they interacted with their Facebook pages.

C.2 In-person political participation

Table C.13: CACE: Effect of home Wi-Fi access on in-person political participation

	In-person participation		
	Local	Municipal	Party
Received WiFi	0.062** [0.030]	0.076** [0.033]	0.011 [0.030]
Outcome range	[0,1]	[0,1]	[0,1]
Control SD	0.306	0.290	0.335
Control mean	0.293	0.093	0.202
First-stage coef.	0.881	0.881	0.881
Hypotheses	two	two	two
Observations	562	561	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: Estimates are complier average causal effects (CACE) obtained via two-stage least squares (2SLS), instrumenting actual Wi-Fi installation with random Wi-Fi assignment. CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). This table disaggregates the *In-person participation* index into its constituent governance levels. *Local* captures attending community or ward councilor meetings and complaining to ward officials in person. *Municipal* captures complaining to the municipality or mayor in person. *Party* captures attending party political meetings and complaining to political parties in person.

C.3 Internet usage

Table C.14: CACE: Internet usage outcomes

	Time online	Uses home router	Internet usage	Owns device	Last seen on WhatsApp
Received WiFi	0.117** [0.067]	0.082** [0.044]	0.084** [0.048]	-0.018 [0.018]	0.093 [0.463]
Outcome range	log(1 + hours)	[0,1]	[0,1]	[0,1]	log(1 + minutes)
Control SD	0.696	0.417	0.499	0.184	2.424
Control mean	0.591	0.222	0.544	0.401	4.958
First-stage coef.	0.881	0.881	0.881	0.881	0.881
Hypotheses	upr	upr	upr	upr	lwr
Observations	561	562	562	562	137

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Note: Estimates are complier average causal effects (CACE) obtained via two-stage least squares (2SLS), instrumenting actual Wi-Fi installation with random Wi-Fi assignment. CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Time online* is the log-transformed total hours spent using the internet (in 1.5 hour increments), measured via a time use survey. *Uses home router* indicates whether the respondent uses a home Wi-Fi router to access the internet. *Internet usage* is a self-reported indicator of using the internet more than once per day. *Owns device* is an index of smartphone, tablet, and computer ownership. *Last seen on WhatsApp* is the average log-transformed time (in minutes) since last WhatsApp activity, measured via metadata tracking; lower values indicate more recent activity.

C.4 News consumption and misinformation exposure

Table C.15: CACE: News Consumption and Misinformation Exposure

	Social media time	WhatsApp usage (tracked)	News via family/friends	WhatsApp preload	News via social media	News via large groups	News frequency	Internet for news	Traditional media	In-person news	Follow MK on FB	MK knowledge
Received WiFi	0.021	0.093	0.005	0.012	-0.030	-0.076*	0.029	-0.009	0.024	0.067*	0.000	0.026
	[0.155]	[0.463]	[0.042]	[0.048]	[0.038]	[0.043]	[0.027]	[0.036]	[0.037]	[0.034]	[0.026]	[0.026]
Outcome range	log(1 + hours)	log(1 + hours)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)	(0,1)
Control SD	1.622	2.424	0.447	0.487	0.390	0.451	0.275	0.382	0.365	0.360	0.281	0.279
Control mean	3.854	4.958	0.593	0.382	0.735	0.467	0.636	0.620	0.702	0.731	0.086	0.516
First-stage coef.	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881
Observations	562	137	562	558	562	562	562	562	562	562	535	562

Signif. Codes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Note: Estimates are complier average causal effects (CACE) obtained via two-stage least squares (2SLS), instrumenting actual Wi-Fi installation with random Wi-Fi assignment. CR2 standard errors clustered at the household level in brackets, p-values are based on randomization inference (RI). *Social media time* is self-reported time spent on WhatsApp, Facebook, YouTube, and TikTok. *WhatsApp usage (tracked)* is the average log-transformed time since last WhatsApp activity, measured via metadata tracking. *News via family/friends* captures learning news via social media from family or friends. *WhatsApp preload* indicates automatic downloading of media on WhatsApp. *News via social media* captures learning news via social media platforms. *News via large groups* captures learning news via large social media groups or influencers. *News frequency* measures how frequently the respondent follows local or national news. *Internet for news* indicates using the internet to learn about events. *Traditional media* captures learning news via TV and radio. *In-person news* captures learning news through in-person interactions. *Follow MK on FB* indicates following the MK party on Facebook. *MK knowledge* is an index of knowledge about MK party platforms and candidates.

D Time Use Measurement

D.1 Survey instrument

To measure how respondents allocate their time, the endline survey asked each respondent to recall a randomly selected day from the previous week and report what they did during six consecutive three-hour windows covering an 18-hour day. For each window, respondents could report up to two activities in their own words and indicated whether each activity took place at home or elsewhere, yielding a maximum of 12 free-text activity descriptions per respondent.

D.2 Activity classification

As pre-registered we classified each free-text activity report into nine pre-specified non-mutually-exclusive boolean categories: unpaid care work, domestic work, paid work, job search, personal care, education, socializing, personal leisure, and internet usage. In addition to these nine pre-registered categories, we coded eight exploratory categories to provide a more granular picture of respondents' time use: social media usage, internet entertainment, radio, television, video entertainment, watching sports, time with family, and household issues.

Following our pre-analysis plan, we employed two independent coding methods. First, we automated the classification using a large language model (OpenAI GPT) with structured JSON output. Each activity was sent to the model along with a detailed system prompt defining all categories and providing classification rules and worked examples. The model returned a JSON object with a boolean field for every category, enforced via a strict JSON schema so that the output always contained exactly the expected fields. Activities were processed in batches with parallel requests and automatic retries for transient API failures, and all results were checkpointed to disk to allow resumption. Second, two undergraduate research assistants independently coded a training set of activities using the same category definitions. One of the authors also coded the same training set to produce a researcher-coded golden set.

As pre-specified, we evaluated pairwise intercoder reliability across the three codings (LLM, RA 1, RA 2) and the golden set using the micro-averaged Hamming loss score, which measures the fraction of category–item decisions on which two coders disagree. Following the decision rule in the pre-analysis plan, LLM classifications were adopted when the Hamming loss between the LLM and at least one human coder was lower than the loss between the two human coders, or when LLM–human disagreement did not exceed 0.1 even if the two human coders agreed more closely with each other. To convert the classified activities into time-use measures, each activity flagged for a given category contributes 1.5 hours (half the three-hour window) to the respondent's total for that category. All time-use totals are log-transformed ($\log(1 + \text{hours})$) to reduce skewness.