Is the IMF a Scapegoat?
A survey experiment in Kenya

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Abstract

Many scholars and practitioners have proposed that leaders find utility in blaming the IMF for stabilizing economic reforms. This "scapegoat" hypothesis has long been used to explain IMF intervention in the Global South. However, there is limited evidence that these tactics are effective in shifting citizens' blame onto the IMF, or that they protect the government from negative public responses like protest or electoral punishment. This research note seeks to test the microfoundations of the scapegoat hypothesis via a survey experiment fielded in Kenya. Our study provides two insights. First, we find that blaming the IMF for structural adjustment has small but significant effects on incumbent support. However, this effect diminishes when respondents are also exposed to counter-narratives in which the opposition blames the government. Second, we find that blame is not zero-sum. While blaming the IMF increases respondents' blame attribution to the IMF, it doesn't reduce the blame placed on the incumbent. Overall the results question the political utility of the scapegoating strategy in a politically competitive environment and highlight that an implicit assumption in the scapegoating argument, zero-sum blame, lacks empirical support.[1]

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Governments borrowing from the International Monetary Fund (IMF) frequently resort to blaming the Fund for implementing unpopular economic reforms. A senior IMF official noted that blaming the IMF is a recurring pattern in numerous countries, often serving as a politically convenient narrative. This official emphasized the consequential nature of scapegoating, with the IMF assuming the role of a scapegoat in the public eye, making the organization's work challenging and requiring resilience (Interview with senior IMF official, 2022). This anecdotal evidence reflects a long-standing hypothesis in the literature on IMF lending, first proposed by Remmer (1986), that leaders blame the Fund for costly economic reforms, thereby avoiding public backlash that may endanger their tenure in office. A government may prefer to consolidate public debt and reforms may be imminently necessary to avoid a crisis, but strong opposition from key interest groups or the general public threatens the government's survival should it implement harsh tax increases and spending cuts. In this case, a government may invite the intervention of the pro-consolidation IMF and attempt to shift the blame for reforms onto the Fund. By framing the Fund as the driver of reforms and convincing voters that it is powerless to refuse IMF intervention, the government may achieve fiscal stabilization without paying the price of public support.

While scapegoating the IMF is a well-established hypothesis in IMF research (Remmer, 1986; Vaubel, 1986; Edwards and Santaella, 1993; Vreeland, 2003; Bird and Willett, 2004), few studies have delved into the logic of the argument, let alone empirically tested the effectiveness of governments' scapegoat strategies. Much work theorizes that blame avoidance is a key reason for governments to agree to IMF intervention (Dreher and Walter, 2010; Rickard and Caraway, 2019), and yet no research has tested whether voters are actually susceptible to this strategy, much less whether blaming the IMF can influence outcomes like support for the incumbent, vote choice, or protest that matter for government survival.

Existing contributions that aim to empirically assess the scapegoat hypothesis often rely on rudimentary indicators, such as election outcomes and observational public opinion surveys (Dreher and Vaubel, 2004; Smith and Vreeland, 2006; Alcañiz and Hellwig, 2011; Williams, 2012; Kosmidis, 2018). While a good first start, these studies are limited in their ability to effectively address endogenous selection while maintaining sufficient statistical power. As such, our understanding of how effective governments are in displacing responsibility to the IMF remains severely constrained. Understanding IMF scapegoating is crucial, as the legitimacy of reform programs hinges on the perceptions of those affected by them, and the political processes through which they are implemented. Additionally, the ability of governments to effectively shift responsibility for these policies to the IMF has substantial implications for their democratic accountability to their citizens.

This study presents the first true test of the effectiveness of IMF scapegoating at the individual level. We present the findings from online survey experiment fielded on 2,000+ Kenyan citizens in December 2023/January 2024, representative of the population in terms of age, gender, and region, recruited via a Facebook advertising campaign. The use of an original survey experiment helps resolve issues of endogenous selection that threaten the inferences of previous studies. It also allows us to have greater control of the treatment and outcomes to measure key intervening variables on the path from IMF Blame to incumbent support.

The analysis reveals two key insights that questions the utility of blaming the IMF unpopular economic reforms. First, we find that a fictional news article blaming the IMF for economic reforms has a small but significant effect (d=0.10) on support for the Kenyan incumbent, William Ruto. However, when respondents are also presented with a counter-narrative in which the opposition blames the incumbent, the treatment effect all but disappears (d=0.05). As such, the finding raises questions about the ability to blame the IMF in the presence of an opposition that will, most likely, want to lay blame at the feet of the incumbent.

Second, we find that blame is not a zero-sum good. Our main treatment was successful at increasing blame for the IMF (d=0.40) among our respondents when asked about blame for the IMF independently and in a forced choice between the IMF and Ruto. However, this did not reduce blame for the Ruto. The treatment blaming the IMF had no impact on the assignment of blame for reforms on Ruto (d=-0.01). This suggests that an implicit assumption that increasing blame for the IMF reduces blame for the incumbent maybe unwarranted. There appears to be enough blame to go around in Kenya.

Hypotheses

We propose and test several hypotheses about the effect of blame-attribution on incumbent support to test the implications of the "scapegoat" effect in the context of IMF structural adjustment. The first and primary hypothesis considers that blaming the IMF for economic reforms can have a successful scapegoat effect that protects the incumbent from negative voter reactions. This expectation is consistent with the IMF scapegoat literature that suggests governments may invite IMF intervention for the express purpose of avoiding blame for costly, but necessary, structural adjustment (Remmer, 1986; Vaubel, 1986; Edwards and Santaella, 1993; Vreeland, 2003; Bird and Willett, 2004). When responsibility for reforms is attributed to the IMF rather than to the incumbent, support for the incumbent should increase.

Hypothesis 1. Primary Hypothesis: *Individuals will be more supportive of the incumbent when responsibility for structural adjustment is attributed to the IMF.*

In reality, public discourse surrounding economic policy is unlikely to be so straightforward as to either blame government leadership *or* the IMF for the costs of structural adjustment. In a second hypothesis we consider that the political opposition may attempt to undermine the incumbent's "scapegoat" efforts and encourage voters to punish the government for costly economic policy. Here, we consider the more realistic scenario where the incumbent blames the IMF for reforms, but the opposition also disputes IMF responsibility and blames the government for reforms. In this divided narrative, support for the incumbent should be higher than when reforms are framed as the responsibility of the government alone, but lower than when the government attributes responsibility to the IMF.

Hypothesis 2. *Individuals will be less supportive of the incumbent when responsibility for structural adjustment is attributed to the IMF and when the opposition blames the government for reforms.*

We further hypothesize about the mechanism responsible for a change in incumbent support, and expect that framing structural reforms as the responsibility of the IMF causes individuals to shift their blame attribution away from the incumbent.

Hypothesis 3. *Individuals will be less likely to blame the incumbent for structural adjustment when responsibility is attributed to the IMF.*

Survey design

We test our hypotheses in Kenya in late December 2023 and early January 2024. Kenya provides a useful setting for several reasons. First, Kenya is currently under an IMF program with conditions that require austerity measures including tax increases and spending cuts. Like most of the Global South at this time, the Kenyan population was wrestling with higher food and fuel prices due to global inflation and wars in Ukraine and the Middle East. As such, the austerity has proven politically contentious and sparked a number of violent protests by supporters of the opposition (Auvinen, 1996; Ortiz and Béjar, 2013; Reinsberg et al., 2023).

Notably, the responsibility for the measures has largely been attributed to William Ruto, the incumbent, in the popular press. Further, Ruto has done little to blame the IMF for the measures when addressing the public or the media. For the purposes of testing the IMF scapegoating hypothesis, this serves two purposes. First, citizens are aware of the austerity and the impact it is having on their lives. As such, the survey touches on a topic all citizens have close familiarity with. Second, there is little evidence that the public has been pre-treated with a story in which the IMF is to blame and Ruto is carrying out a policy that he does not support.

To test our three hypotheses, respondents will be randomly assigned to one of three treatment arms where they are shown fictional excerpts of newspaper articles. These articles are formatted to resemble news stories published online by *The Daily Nation*, Kenya's largest English-language daily newspaper.[2]

One-third of respondents assigned to the "control" group are shown an article, Figure ??, that describes the need for the Kenyan government to implement a new round of economic reforms. One-third are assigned to the "IMF blame" treatment and are shown a similar article, left panel in Figure 2, that describes the economic reforms as mandated by the IMF and that the government has little choice but to enact the reforms. One-third are assigned to the "IMF-government blame" treatment and are shown an article, right-panel Figure 2, that frames reforms as IMF-mandated, but also discusses how the political opposition attributes responsibility to the government.

Treatments

Following the treatment articles, we asked our respondents whom they attribute blame for austerity measures. We asked about blame in a forced choice (IMF, Ruto, Don't Know) but also asked about blame attribution independent of other targets: "How responsible do you think President William Ruto is for the recent tax increases and reduction in fuel subsidies?" (11-point scale, Not responsible - Completely responsible). The outcome of this question is

[2] A timer is set for each vignette so that respondents are unable to navigate beyond the newspaper article for at least 10 seconds.

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Government announces more tax increases and cuts to fuel subsidies

Wednesday, December 20, 2023

The Kenyan Government is having trouble paying its bills. To improve the budget balance, new tax increases and spending cuts have been announced.

President William Ruto increased the VAT (value added tax) and reduced fuel subsidies in May 2023. These measures were extremely painful for Kenyan citizens. However, these efforts were not enough to fix the budget, and the government will raise taxes and cut spending for the second time this year.

Figure 1: **Control:** The control is shown to 33% of respondents and preceded by this sentence: "This is an excerpt from a newspaper article published on December 20, 2023. **Please read it carefully.** We will ask questions about the contents."

used to test Hypothesis 3. We also asked a similar question about how much responsibility respondents attribute to the IMF as a further manipulation check. We expect those that receive the treatment to attribute more blame to the IMF than those in the control group.

Following the questions on blame attribution, we asked our respondents four questions about their assessment and vote intention for William Ruto. We use these four questions to create an additive index of *Incumbent Support* to test Hypotheses 1 and 2. These incumbent support questions are based on those constructed by Schleiter and Tavits (2018). The construction of an index aims to increase precision in estimation of individuals' attitudes towards the incumbent by reducing measurement error. This index variable ranges from 0 (low approval) to 44 (high approval) but we standardize the variable for a mean of 0 and standard deviation of 1 in our analysis.[3]

[3] A timer is set for each question so that respondents cannot navigate beyond the question for at least 4 seconds.

(a)

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IMF demands more tax increases and cuts to fuel subsidies

Wednesday, December 20, 2023

The Kenyan Government is having trouble paying its bills. The IMF (International Monetary Fund) has offered to help, but only if the government increases taxes and cuts spending to improve the budget balance.

President William Ruto agreed to IMF conditions in May 2023 and increased the VAT (value added tax) and reduced fuel subsidies. These measures were extremely painful for Kenyan citizens. However, the IMF is now demanding more reforms, and asked the government to raise taxes and cut spending for the second time this year.

Government officials say they have no choice but to follow IMF recommendations. They complain that the Western-dominated IMF has huge influence over Kenya since the government needs IMF funds to avoid economic disaster.

(b)

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IMF demands more reforms; opposition blames Ruto

Wednesday, December 20, 2023

The Kenyan Government is having trouble paying its bills. The IMF (International Monetary Fund) has offered to help, but only if the government increases taxes and cuts spending to improve the budget balance.

President William Ruto agreed to IMF conditions in May 2023 and increased the VAT (value added tax) and reduced fuel subsidies. These measures were extremely painful for Kenyan citizens. However, the IMF is now demanding more reforms, and asked the government to raise taxes and cut spending for the second time this year.

Government officials say they have no choice but to follow IMF recommendations. They complain that the Western-dominated IMF has huge influence over Kenya since the government needs IMF funds to avoid economic disaster.

However, opposition critics argue that the Government is still to blame for painful economic policies. Opposition leader Raila Odinga has spoken out against the government, saying that President Ruto is responsible for the economy, not the IMF.

Figure 2: **Treatments:** Each treatment article sent to 33% of respondents. They are preceded by this sentence: “This is an excerpt from a newspaper article published on December 20, 2023. **Please read it carefully.** We will ask questions about the contents.”

We will now ask you for your opinion about President William Ruto. We want to know what you think! Please take your time and read each question carefully.

- "How would you rate the performance of President William Ruto?" 11-point scale from "Very negative" to "Very positive"
- "How would you rate the performance of President William Ruto in managing Kenya's economy?" 11-point scale from "Very negative" to "Very positive"
- "Imagine that presidential elections will be held tomorrow. How likely would you be to vote for William Ruto?" 11-point scale from "Very unlikely" to "Very likely"
- "How well do you think President William Ruto will manage the Kenyan economy in the future?" 11-point scale from "Very badly" to "Very well"

Sampling

We targeted a sample of 2,100 Kenyan adults recruited via a Facebook advertising campaign. Facebook users with accounts registered within Kenya were eligible to be shown an ad which invites them to participate in a short survey, in which they can earn mobile phone minutes ("airtime") as compensation. The ad contained a link to the survey questionnaire, hosted in Qualtrics. Over 11,000 users clicked our link. After respondents were filtered out because of full quotas or other eligibility requirement and duplicate entries were deleted, we have a final sample of 1,946 respondents. We present the balance of demographics across treatment conditions and a comparison with census data in the Supplementary Appendix.

Social media recruitment has several advantages in the Kenyan context. A large share of the population has access to internet and has a social media account, with 98% of adults having access to a mobile phone (Kharono et al., 2022) and 49% with a Facebook account. While mobile phone and social media use skews towards wealthier, highly educated urban citizens, this is also a problem when recruiting online respondents from the panels of traditional survey companies in the region. Recruitment via Facebook allows access to a wide pool of respondents at a low cost. This sampling approach is similar to those previously used by Rosenzweig and Zhou (2021) and Pham et al. (2019) to recruit online survey respondents in sub-Saharan Africa.

Our recruitment ad was shown to Facebook accounts registered in Kenya to users above 18 years of age and was displayed to users until 2,100 complete survey responses have been collected. Ads are not assigned randomly. Instead, Facebook shows to an audience most likely to click on the link within the ad as determined by the Facebook advertising auction system algorithm. Further, the ad was targeted separately to male and female users, and to users based on broad age categories derived from the results of the 2019 Kenyan census.[4] This targeting approach follows the recommendations outlined in Neundorf and Öztürk (2023), where the authors find that maximizing link-clicks and targeting ads along broad demographic quotas like age and gender can improve representation in the sample.

We set nationally representative quotas in Qualtrics for age, gender, and region. We screened out respondents after these quotas are filled. In line with previous survey research via social media in developing countries (Rosenzweig and Zhou, 2021; Pham et al., 2019), we expect our Facebook sample to be skewed towards urban, highly educated, and wealthier citizens and so will not attempt to achieve a nationally representative sample along these attributes. Further, the survey and recruitment was presented in English. English is a compulsatory subject in Kenyan schools and an official language along with Swahili. Still, there maybe a population of Swahili only reading or non-literate population that is necessarily excluded from our quota sample. As such, the survey excludes the small amount of Kenyans that do not read English.

Respondents were compensated for their participation with Ksh. 100 (€0.60) airtime minutes via text message. While ethical, providing compensation creates incentives for mul-

[4] 40% 18-30 yrs, 24% 31-40 yrs, 16% 41-50 yrs, 20% ¿50 yrs, see https://knbs.or.ke/visualizations/?page_id=3126

tiple responses and sharing with like-minded friends. We used several strategies to ensure that individuals only take the survey once, and to guard against the survey link being redistributed outside of the Facebook advertising platform. First, we activated Qualtrics fraud detection, which attaches a cookie to the user's browser, preventing the same device-browser combination from submitting subsequent survey responses. Second, we discarded responses that submit the same telephone number for compensation as has already been submitted in a previous response. Third, we discarded responses that had identical responses on four categories (IP Addresses, Sex, Region, Age). In developing countries it isn't uncommon to have responses from the same IP addresses as mobile providers will use the same IP for multiple users. As such, we only discarded responses that were similar on additional dimensions.[5] Lastly, we screened our respondents that indicated they received a survey link from anywhere other than a "Facebook advertisement".

Analysis

Figure 3 presents the average treatment effect (ATE) estimated by OLS and complier average causal effect (CACE) estimated using two-stage least squares. The later used the randomized treatment as an instrument for whether or not the respondent "recieved" the treatment. We codify this as being able to correctly identify the fictitious article name post-treatment. This has the added benefit of allowing us to test the effect on those that were paying attention without having to drop results based on post-treatment attention checks or attention checks unrelated to the treatment.

In both models, we included a matrix of pre-treatment covariates and their coefficients on the right hand side $\boldsymbol{\lambda}\mathbf{D}$. We chose these variables agnostically with a LASSO selection model following the recommendation of Bloniarz et al. (2016). We include each continuous

[5] This condition was not preregistered but was deemed necessary after the first look of the survey. We disgarded 503 responses and recollected the equal amount of respondents after resetting quotas.

variable individually and each categorical variable as dummies in a model predicting the outcome. The LASSO model returns only variables with non-zero coefficients. We then include these non-zero variables in our model estimating treatment effects. This has the benefit of increasing the precision of our estimates (i.e. increasing power) in a way that does not increase researcher degrees of freedom.

The top panel of figure 3 demonstrates a small but significant ATE and CACE. Since the dependent variable is standardized (mean=0, SD=1), both estimates can be interpreted as a percentage of a standard deviation. Compared to the control group, those shown an article blaming the IMF for reforms demonstrate 7% or 10% of a standard deviation higher support for the incumbent. These are small effects but it is important to keep in mind that the treatment is quite tame compared to repeated exposure to blame narrative citizens may experience in real life.

The bottom panel tests hypothesis 2 by comparing the control group to the group that received an article blaming the IMF *and* noting that the opposition blames the incumbent. Here we see that the already small point estimates are almost cut in half and the statistical significance is not retained. This suggests that the opposition blame can successfully counter the government's narrative. As we show in the supplementary appendix, this appears to hold for both previous voters of Ruto and Opposition alike. We found no substantive differences in the treatment effects across political support.

To further probe our results, we look at the ATE when estimating the effect on each component of the additive index. Figure 4 presents these findings. We see that the largest and most significant effect for the outcome positing a hypothetical vote for the incumbent, Ruto, in the next election. The ATEs for the remaining outcomes are insignificant, but inline with the direction and magnitude of the overall index. As such, we have grater confidence the the small effect sizes presented Figure 3 is not due a negative relationship with one

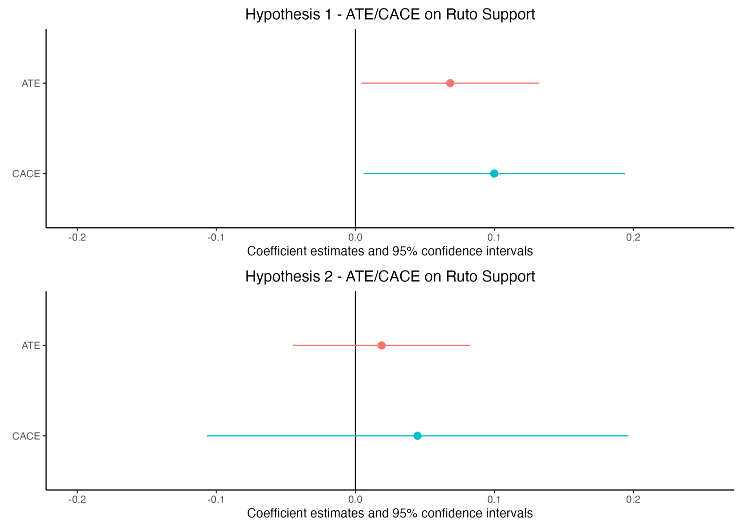

Figure 3: Tests of Hypothesis 1 and 2

component of the index.[6]

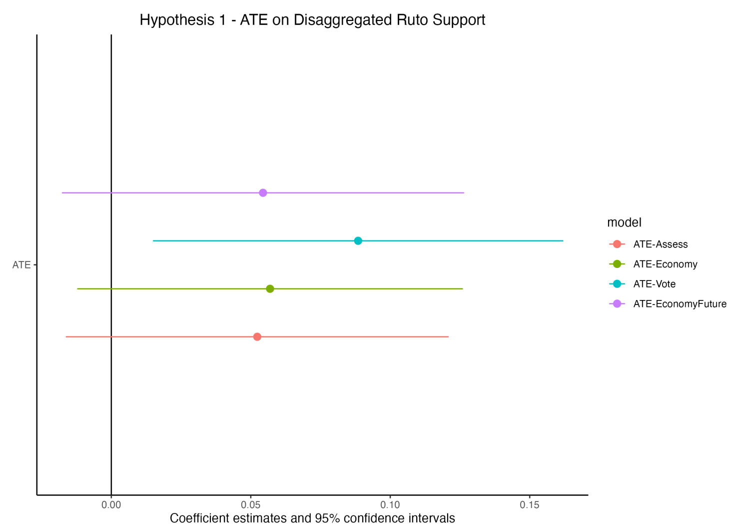

Figure 4: ATE: Each Index Component

Next, we pay closer attention to the path from blame to support by looking directly at blame attribution for the economic reforms. Hypothesis 3 states expectations regarding blame of the incumbent as a function of the treatments. Recall that we asked two questions

[6]It isn't surprising that 3 of the 4 coefficients are insignificant. The goal of the index was to increase power by reducing measurement error. Thus significance is more likely with the addiditive index than with each outcome estimated independently.

about blame. One asked about blame and gave a choice (IMF, Ruto, Don't know). We simply coded this answer in to a binary outcome blame for IMF and blame for Ruto leaving the remaining categories in the baseline. The panels on the right of Figure 5 present the estimates based on linear probability models comparing IMF blame treatment to the control condition. The second measure of blame results from two questions in which we inquired about blame for the reforms on a 0-10 scale for the IMF and Ruto separately. The results of these analyses can be seen on left of Figure 5.

We see that when given a choice, the blame IMF treatment (compared to the control condition) has a reduces blame placed on Ruto by 12%(ATE) - 20%(CACE). However, when asked to simply place blame on 0-10 scale, the treatment does not have a statistically significant effect. Again, the scale is standardized, as such the effect sizes are interpreted as a percent of standard deviation. The null effect of blame on Ruto may be a function of the treatment not working (despite our results above). However, the bottom panels of 5 indicate that the treatment has a sizeable effect on blame towards the IMF in both the scale outcome (0.3-0.4) and the choice outcome (14 to 20%). Consequently, this is a strong indication that the treatment was successful and that the null effects on blame toward Ruto were not a function of an weak treatment.

Before unpacking these results, we briefly draw attention to the comparison between the 2nd treatment condition and the control on the blame outcomes in Figure 6. We first see that the 2nd treatment isn't successful in producing significant effects on either blame for Ruto or blame for the IMF when using the scale outcomes. This is consistent with the test of the first hypothesis in which the opposition blame attenuates efforts to blame the IMF. However, we do see that the treatment does impact blame when respondents are forced to choose between the IMF and Ruto albiet with a smaller maginitude than the initial treatment.

What does this mean? We interpret the difference between the forced choice and the scale outcomes as evidence that blame is not necessarily zero-sum. While blaming the IMF might increase the degree by which voters hold the IMF responsible for reforms it doesn't follow that they will reduce blame on other actors.

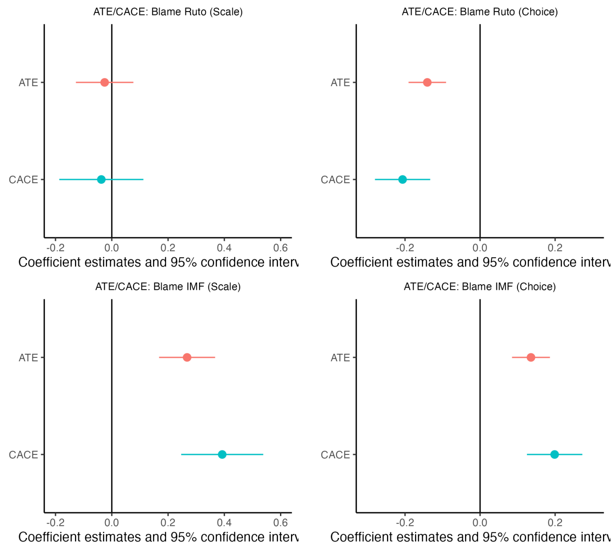

Figure 5: IMF Treatment and Blame

Discussion & Conclusion

Despite playing a large role in explaining why countries invite IMF intervention, evidence that scapegoating is effective is both scarce and suffers from severe methodological limitation. We tried to remedy these issues by directly studying this phenomenon by randomly varying blame attribution for economic reforms in fictitious news reports.

Our study is not the final word on this subject. There are several limitation that future research would be wise to address. First, our study was conducted in Kenya during a time when it was currently under and IMF program with the potential for greater Fund involvement. Further research might be wise to time the survey experiment with the roll-out IMF backed reforms. It remains possible that IMF scapegoating decays as time goes on.

Lastly, a single survey experiment shouldn't be the final word on a subject. The effect may emerge in different contexts. For example, we found little evidence of conditional

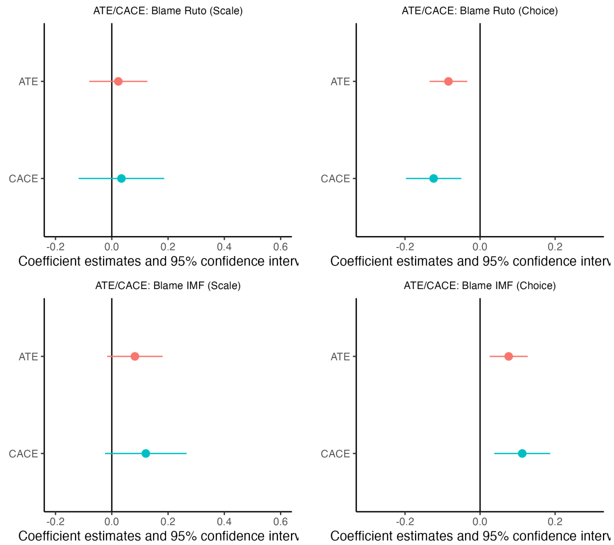

Figure 6: ATE: Each Index Component

treatment effects across supporters of the incumbent and opposition. However, the utility of the IMF scapegoating may be conditional on the identity of the incumbent. For obvious reasons, we couldn't randomize the incumbent, in our study. However, future studies may seek to examine if IMF scapegoating works better when the incumbent has a more credible claim to oppose these reforms. In our case, Ruto did appear during campaigning as being an advocate for working classes given his 'hustler-in-chief' reputation. However, that image changed as he became more supportive of the benefits of reform.

Further, a key finding our study shows that the opposition can counter IMF scapegoating. Future studies would be wise to study the effect in environments where the opposition does not have the freedom or credibility to express blame. If our results are a guide, the scapegoat effect may have more mileage in non-competitive political environments.

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Appendix

Dependent Variables

Blame Attribution: To test if the treatments have manipulated blame for the austerity policies, we first ask questions regarding responsibility for economic reforms. These outcomes are also useful for exploratory research to examine if the treatments influence attribution of blame but do not extend to changes in overall presidential approval.

- "How responsible do you think President William Ruto is for the recent tax increases and reduction in fuel subsidies?" (11-point scale, Not responsible - Completely responsible)
- "How responsible do you think the International Monetary Fund (IMF) is for the recent tax increases and reduction in fuel subsidies?" (11-point scale, Not responsible - Completely responsible)
- "Who do you think is **most** responsible for the recent tax increases and reduction in fuel subsidies?" (The International Monetary Fund, William Ruto, Don't know)
- "There have been massive protests in recent months against the policies to raise taxes and reduce fuel subsidies. These protests have often turned violent, with widespread destruction of property and looting. Who do you believe is most responsible for this violent unrest?" (President William Ruto, The International Monetary Fund, Opposition leader Raila Odinga, Other)

Presidential Approval Index: Our central dependent variable is an additive index variable based on several questions aimed at capturing approval of President Ruto. These incumbent support questions are based on those constructed by Schleiter and Tavits (2018). The construction of an index aims to increase precision in estimation of individuals' attitudes towards the incumbent. This index variable ranges from 0 (low approval) to 44 (high approval). A timer is set for each question so that respondents cannot navigate beyond the question for at least 4 seconds.

- "We will now ask you for your opinion about President William Ruto. We want to know what you think! Please take your time and read each question carefully."
- "How would you rate the performance of President William Ruto?" 11-point scale from "Very negative" to "Very positive"
- "How would you rate the performance of President William Ruto in managing Kenya's economy?" 11-point scale from "Very negative" to "Very positive"
- "Imagine that presidential elections will be held tomorrow. How likely would you be to vote for William Ruto?" 11-point scale from "Very unlikely" to "Very likely"

- "How well do you think President William Ruto will manage the Kenyan economy in the future?" 11-point scale from "Very badly" to "Very well"

Quasi-Behavioral Outcome: To examine if the treatments impact intentions beyond approval, we ask respondents about their willingness to sign a petition against the IMF and Government. We then take the difference between the petition responses to indicate how willing individuals are to signal disapproval of the IMF relative to the government.

- Would you be willing to sign a petition (at the end of this survey) asking **the government** to reverse the cuts to government spending? 11-point scale from "Very unwilling" to "Very willing"
- Would you be willing to sign a petition (at the end of this survey) asking the **International Monetary Fund** to reverse the cuts to government spending? 11-point scale from "Very unwilling" to "Very willing"

Finally we ask if respondents would be willing to join a protest against the IMF.

- "How likely would you be to join a protest against the International Monetary Fund in the future?" 11-point scale from "Very unlikely" to "Very likely"

Post-treatment

- Randomized attention checks: respondents are randomly shown one of the following four questions:
  - "People are very busy these days and many don't have time to find the best price for products. There are many websites that offer the same product at very different prices. Some have time to browse products all day, but others don't even have time to read the questions carefully. To show that you've read this far, ignore the question below and just type the word "green" in the text box below. How many websites do you visit to compare prices before finally purchasing a product?"
  - "We care about the quality of our survey data. It is very important for our research that we collect accurate measures of your opinion. We hope that you will provide honest, thoughtful answers to all questions in this survey. So far, have you provided honest, thoughtful answers to the questions in this survey?" (No, my answers have not been honest / I cannot say either way / Yes, all my answers have been honest / Yes, but only some of my answers have been honest)
  - "We are interested in how often citizens use financial services like online banking and in-person banking. Some people have multiple bank accounts, while others only have one bank account, or none at all. Some only use banking services in person, while others do all of their banking online or via their mobile phone. To show that you are paying attention, ignore the question below and just select the number eight. How many bank accounts do you have? "

  - "Read the text below: The day began with a clear blue sky with white clouds. The group started on their journey and soon arrived in a small village. They saw that bright green grass surrounded a large house on the hill. Which colors are **not** mentioned?" (Red / White / Green / Blue / Yellow)

- Informational attention check: All respondents are asked a question to capture whether they were paying attention to the newspaper article treatments. **Note:** The first question below was asked to the first 100 respondents in the survey, collected during the soft-launch on 21 December 2023 conducted prior to the registration of this PAP. These responses indicated that the question wording was unclear and would not accurately capture differences in attention across treatment arms. As a result, this was replaced with the second question, which will be asked to the remaining 2,000 respondents.
  - (Attention check, soft-launch only) "You were asked to read an article about the Kenyan economy. What information was included in the article?" (The government will lower income taxes, the government wants to increase taxes and cut fuel subsidies, the IMF is pushing the government to increase taxes and cut fuel subsidies, the unemployment rate is increasing).
  - (Attention check) "You were asked to read a newspaper article about the Kenyan economy. What was the title of that article?" (Government announces decrease in public sector employment / IMF demands more tax increases and cuts to fuel subsidies / Government announces more tax increases and cuts to fuel subsidies, / Unemployment expected to increase in 2024 / IMF demands more reforms; opposition blames Ruto)

- "How did you access this survey? Please be honest! You will still receive Ksh. 100 airtime no matter which option you choose." (Facebook advertisement / Received the link from a friend / Whatsapp advertisement / Other / Facebook post / Instagram advertisement)

- (Debrief) "Thank you for completing this survey. Your response has been recorded anonymously. The newspaper article that you were shown was fictional and was created by our research team only for the purposes of this survey. However, the information in this article was accurate and describes real changes in Kenyan economic policy.
  To thank you for your time, **we would like to offer you Ksh. 100 of airtime**. Enter your phone number below to receive your airtime within 24 hours, then click Next. If you do NOT want to receive airtime, click Next."

Pre-treatment questions

Respondents are screened out of the survey if they answer "I do not agree" to the consent form (first question) or if they do not answer "Facebook advertisement" to the second question.

- (Consent)
  “Thank you for agreeing to take part in this study. This is a 7-minute survey about the Kenyan economy. Please answer all questions completely. **You can only take this survey once.**

  To thank you for your time, **we will send you Ksh. 100 of airtime at the end of the survey**. We will ask you for your phone number to transfer the airtime, but we will not contact you again, an will not keep any record of your phone number.

  The data collected in this survey are completely anonymous and will be used for academic research. Your participation in this study is totally voluntary and you can withdraw your response at any time.

  We will use the data to conduct statistical analysis and draw general conclusions. Anonymous data will only be shared with third parties upon publication of any article resulting from the project. No individual respondent will be identified.

  By clicking ”I agree” you indicate that you are at least 18 years old, have read and understand this statement, and agree to take part in this research survey.”

  (I agree, I do not agree)

- “How did you access this survey? Please answer honestly.” (Facebook advertisement, Instagram advertisement, Received the link from a friend, Other)
- “What is your current mobile service provider?” (Safaricom, Airtel Kenya, other)
- “How old are you?”
- “What is your gender?”
- “Which county do you live in?” (List of 47 counties)
- “What is your highest level of education?” (8-level scale from “No formal schooling” to “Post-graduate degree”)
- “What is the average monthly income of your household?” 8-point scale from “Less than Ksh. 1,200” to “More than Ksh. 30,000”
- “What is your opinion of President William Ruto?” 11-point scale from “Very negative” to “Very positive”

- “What is your opinion of opposition leader Raila Odinga?” 11-point scale from “Very negative” to “Very positive”
- “Have you ever heard of the International Monetary Fund (IMF) (Yes/No/not sure)”
- “What is your opinion of the International Monetary Fund (IMF)?” 11-point scale from “Very negative” to “Very positive”
- “Who did you vote for in the 2022 presidential election?” (William Ruto, Raila Odinga, Other, I did not vote / Prefer not to say)
- “Do you agree or disagree with the following statements?” [5-point scale strongly agree - strongly disagree]
  - “The government budget is too large and the government needs to cut spending”
  - “The government needs to cut spending to repay Kenya’s large debt”
  - “The government needs to increase taxes to repay Kenya’s large debt”

Estimation & Sampling

Sampling

We will draw on a sample of 2,100 Kenyan adults recruited via a Facebook advertising campaign. Facebook users with accounts registered within Kenya will be shown an ad which invites them to participate in a short survey, in which they can earn mobile phone minutes (“airtime”) as compensation. The ad contains a link to the survey questionnaire, hosted in Qualtrics.

Social media recruitment has several advantages in the Kenyan context. A large share of the population has access to internet and has a social media account, with 98% of adults having access to a mobile phone (Kharono et al., 2022) and 49% with a Facebook account. While mobile phone and social media use skews towards wealthier, highly educated urban citizens, this is also a problem when recruiting online respondents from the panels of traditional survey companies in the region. Recruitment via Facebook allows access to a wide pool of respondents at a low cost. This sampling approach is similar to those previously used by Rosenzweig and Zhou (2021) and Pham et al. (2019) to recruit online survey respondents in sub-Saharan Africa.

First, a Facebook page was established for the organization that will deploy the advertisements. This is the “MiDebt Project,” which refers to the “Microfoundations of Debt Crises” research project under which this survey is being conducted. The page contains accurate information about the project as well as links to the project page on the Leiden University website. The Facebook ad will display the name “MiDebt Project” as the sponsoring organization, and users can navigate to the public MiDebt Project Facebook page directly from the ad.

Second, an advertisement campaign will be launched from the MiDebt Project page. The ad will be shown to Facebook accounts registered in Kenya to users above 18 years of age and will continue to be displayed to users until 2,100 complete survey responses have been collected. The ad will not be shown to a random sample of Kenyan Facebook users, but will be shown to an audience most likely to click on the link within the ad (as determined by the Facebook advertising auction system algorithm). Further, the ad will be targeted to be shown to separately to male and female users, and to users based on broad age categories derived from the results of the 2019 Kenyan census.[7] This targeting approach follows the recommendations outlined in Neundorf and Öztürk (2023), where the authors find that maximizing link-clicks and targeting ads along broad demographic quotas like age and gender can improve representation in the sample.

Figure A1 shows the Facebook ad used for recruitment. This ad is shown to respondents either as a sponsored post within their timeline, or as a sidebar on the margins of a Facebook page.

Once users have clicked on the link, they are redirected to the survey questionnaire. Importantly, the Facebook advertising platform does not provide any granular data on which accounts that view or interact with ads. Thus, there is no way for the research team to connect survey respondents to their Facebook profile, or any personal information therein. Within the survey, respondents will first be asked a series of demographic questions (age, gender, region, income, education). We will set nationally representative quotas for age and gender, and screen out respondents after these quotas are filled. In line with previous survey research via social media in developing countries (Rosenzweig and Zhou, 2021; Pham et al., 2019), we expect our Facebook sample to be skewed towards urban, highly educated, and wealthy citizens and so will not attempt to achieve a nationally representative sample along these attributes.

Respondents are compensated for their participation with Ksh. 100 (€0.60) airtime minutes. This is delivered to them via text message. At the end of the survey, respondents are asked for their phone number in order to receive their airtime balance. Using the Africa's Talking API (`https://africastalking.com/`), we will a send short-code text message to each phone number containing the airtime balance, and the message "Thank you for taking our survey! Here is your Ksh. 100 airtime." This text message appears on respondents' mobile phones as originating from the sender ID "LEIDEN_POL" and respondents are unable to reply to this message. Immediately following the airtime transfer, respondents' phone numbers are deleted (as respondents are informed in the survey consent form).

We use several strategies to ensure that individuals only take the survey once, and to guard against the survey link being redistributed outside of the Facebook advertising platform. First, we will activate Qualtrics fraud detection which attaches a cookie to the user's browser, preventing the same device-browser combination from submitting subsequent survey responses. Second, we will discard responses that submit the same telephone number for compensation as has already been submitted in a previous response. Third, respondents

[7] 40% 18-30 yrs, 24% 31-40 yrs, 16% 41-50 yrs, 20% ¿50 yrs, see `https://knbs.or.ke/visualizations/?page_id=3126`

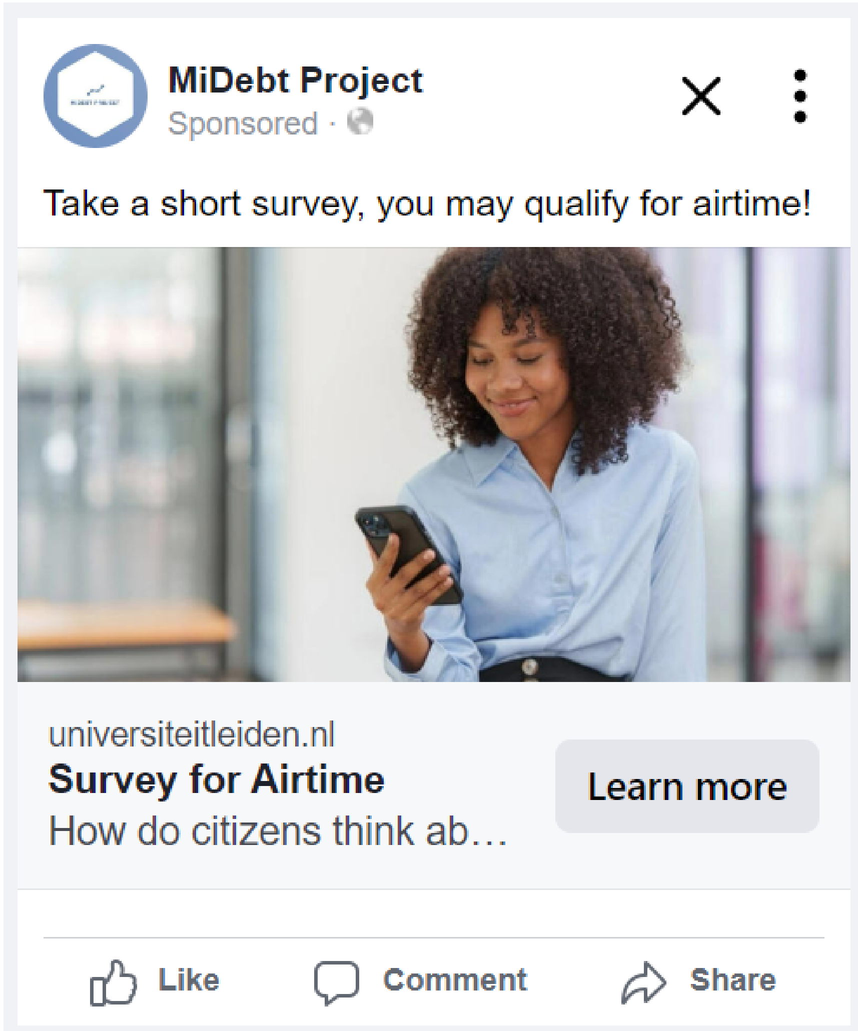


Figure A1: Facebook ad used for respondent recruitment

will be asked at the start of the survey where they accessed the survey link, and those who choose an answer other than "Facebook advertisement" will be screened out.

Data collection begins on 21 December and is expected to take 7 to 12 days. First, 100 responses were collected as a "soft-launch" to ensure that data collection and storage worked as expected. One small change was made following this soft launch: the replacement of one of the attention check questions (see page 14). The survey will be re-opened to collect the remaining 2,000 responses on 22 December following the registration of this PAP.

Pre-registered Exploratory Hypotheses

In addition to our primary hypotheses tested above, we consider several exploratory hypotheses that propose conditional relationships between blame attribution and incumbent support. Hypothesis 4 expects that the treatment will have a stronger effect on fiscal liberals than on fiscal conservatives. Voters who are ex ante fiscally liberal, meaning that they generally oppose spending cuts and tax increases, may strongly disapprove of the conservative fiscal policies needed to balance budgets and often implemented by the IMF. They may be the most likely to blame those responsible for the introduction of reforms, be that the government or the IMF, and so should respond most dramatically to information that identifies the responsible actor.

Hypothesis 4. ***Exploratory hypothesis*** *The IMF-blame treatment will have a stronger effect among those who are fiscally liberal (opposed to spending cuts and tax increases).*

The effect of blame-avoidance may also cleave along partisan lines. Governments may expect a loss of support when implementing structural adjustment, and so use scapegoating strategies to prevent supporters from defecting to the opposition. If this is effective, it would suggest that blame-avoidance has the strongest effect on the incumbent's supporters. These voters may be most receptive to government attempts to frame structural adjustment as an externally-imposed necessity, and thus most likely to shift blame for reforms onto the IMF.

Hypothesis 5. ***Exploratory hypothesis*** *The IMF-blame treatment will have a stronger effect among supporters of the incumbent.*

However, we also consider that the opposite may be true, and that blame-avoidance may have the strongest effect on voters who support the opposition rather than the incumbent. Rather than scapegoating the IMF to retain its current supporters, the government may engage in blame-avoidance to avoid a deepening of the opposition, especially if opposition to reforms may lead to protest or unrest. Opposition supporters have low levels of support for the incumbent by definition, and so blame-avoidance framing is unlikely to suffer from the ceiling effects that may limit the effect of this strategy among the incumbent's supporters.

Hypothesis 6. ***Exploratory hypothesis*** *The IMF-blame treatment will have a stronger effect among supporters of the opposition.*

Estimation

Parameters:

- Y^a = Presidential Approval Index (0-11)
- Y^b = Incumbent blame attribution (0-11)
- G = Government Blame (baseline condition)
- M = IMF blame (Treatment 1)
- C = IMF & government blame (Treatment 2)
- F = Fiscal liberalism

- I = Supports incumbent
- $\boldsymbol{\lambda}\mathbf{D}$ = matrix of pre-treatment covariates and their coefficients

In each equation, we include a matrix of pre-treatment covariates and their coefficients on the right hand side $\boldsymbol{\lambda}\mathbf{D}$. We select these variables agnostically with a LASSO selection model following the recommendation of Bloniarz et al. (2016). Essentially, We include each continuous variable individually and each categorical variable as dummies in a model predicting the outcome. The LASSO model returns only variables with non-zero coefficients. We then include these predicted variables in our model estimating treatment effects.

Hypothesis 1. *estimator: OLS,*
$Y_i^a = \beta_0 + \beta_1 M_i + \beta_2 C_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_1 *is positive and significant.*

Hypothesis 2. *estimator: OLS,*
$Y_i^a = \beta_0 + \beta_1 C_i + \beta_2 G_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_1 *is negative and significant.*

Hypothesis 3. *estimator: OLS,*
$Y_i^b = \beta_0 + \beta_1 M_i + \beta_2 C_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_1 *is negative and significant.*

Hypothesis 4. *estimator: OLS,*
$Y_i^a = \beta_0 + \beta_1 M_i + \beta_2 F_i + \beta_3 (M * F)_i + \beta_4 C_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_3 *is positive and significant.*

Hypothesis 5. *estimator: OLS,*
$Y_i^a = \beta_0 + \beta_1 M_i + \beta_2 I_i + \beta_3 (M * I)_i + \beta_4 C_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_3 *is positive and significant.*

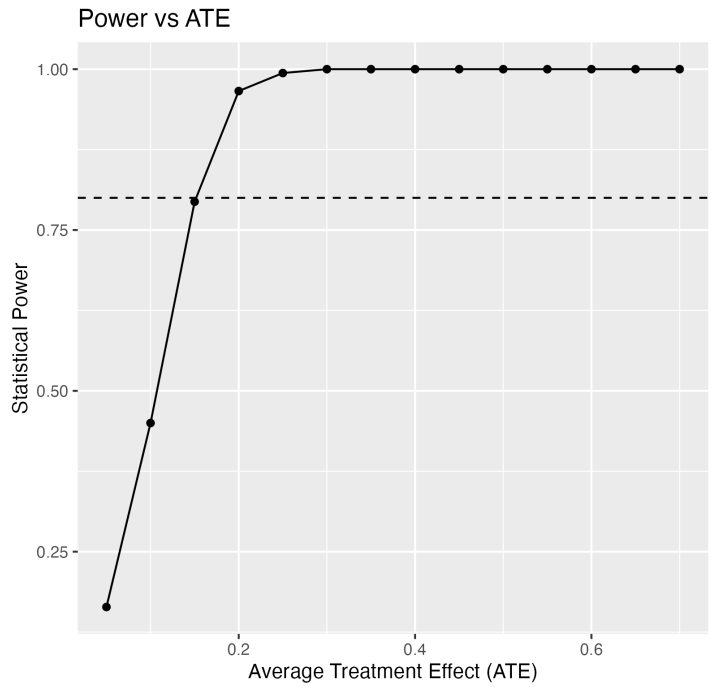
Hypothesis 6. *estimator: OLS,*
$Y_i^a = \beta_0 + \beta_1 M_i + \beta_2 I_i + \beta_3 (M * I)_i + \beta_4 C_i + \boldsymbol{\lambda}\mathbf{D} + \epsilon_i$,
expectation: β_3 *is negative and significant.*

Beyond the Intention to treat effect (ITT) estimand in the above equations, we also look at the complier average causal effect (CACE) to address issues of attention. We estimate this in a two stage equation. To simplify things, we only estimate these equations on two experimental arms and omit observations for irrelevant arms (unlike above). In each tests (H1 and H2), we adopt the following two-staged least squares structure:

$$Comply_i = \gamma_0 + \beta_1 C_i + \boldsymbol{\lambda X}\mathbf{D} + \mu_i \tag{1}$$

$$Y_i^a = \beta_0 + \beta_1 Comply_i + \boldsymbol{\lambda X}\mathbf{D} + \epsilon_i \tag{2}$$

Figure A2: Minimum Detectable Effect (MDE)



Inference criteria

- We estimate our models with HC2 standard errors.
- For our primary hypotheses (1 & 2), we use a two-tailed test.
- we set $\alpha = 0.05$ and will reject the null when the p-value is less than 0.05.
- for our remaining hypotheses estimating Y^a, we adjust for multiple comparisons by running simulations and considering the correlation among the outcomes. See https://egap.org/resource/things-to-know-about-multiple-comparisons/ for more information on this approach.

Power analysis

This power analysis shows the statistical power at various assumed effect sizes (as a percentage of a standard deviation). This power analysis considers comparisons of two arms, just as our primary hypotheses, and thus we hold the sample size at 1400. The analysis in Figure A2 is based on 100 simulations of each effect size using the DeclareDesign Package in R (Blair et al., 2019). We assume a mean of 0 in the control group and a SD of 1 for all treatment arms. It also assumes a correlation of the outcome the additional covariates of $R^2 = 0.3$. A total sample size of 2,100 will yield a minimum detectable effect of about 0.15 at 80% power.