Power Calculations
Part 1

July 5, 2025

Baseline WTA Outcomes for Main Experiment

Our planned analyses of the baseline data on WTA are primarily regressions that examine how WTA is correlated with various factors, and thus are not amenable to standard power calculations. However, we can estimate our statistical power by extrapolating from the estimated standard errors in our pilot data (see https://blogs.worldbank.org/en/impactevaluations/why-ex-post-power-using-estimated-effect-sizes-bad-ex-post-mde-not).

The most straightforward analysis is the relationship between WTA and the difference between the amount of money the respondent allocates to each period and the amount that is allocated under the default. In our pilot data we ran a regression of the log of WTA (via the IHST, with WTA measured in GHS) on AbsDiffShare (in percentage points), so the coefficient can be interpreted as an elasticity. We get an SE of 0.005 with a sample size of 55 (53 degrees of freedom, since there is one d.o.f. used for the regressor and one for the constant). Our full study will have a sample size of 700 (698 d.o.f.). This will scale down the estimated standard error by a factor of sqrt(53/698) = 0.276. So we expect a standard error of 0.014. The MDE at 80% power is 2.8 times the SE, so we will have 80% power to detect an elasticity of at least 0.039.

Restricting our analysis only to the non-Inflation arm, we have a sample size of 350, and 348 d.o.f. In this case we would have an estimated SE of sqrt(53/348)*0.05 = 0.019, and so an MDE for the elasticity of 0.055.

Our power for other analyses will not be this high, but we should be very well-powered for all the primary analyses that we will conduct with the baseline data.

Baseline WTA Outcomes for Cross-Randomized Inflation Treatment

The most straightforward analysis is to look at the treatment effect of the inflation information on $AbsPercentGap_i$,

$$AbsPercentGap_i = \sum_{p=1}^{6} |DiffShare_{i,p}|$$

Where *Diffshare*$_{i,p}$ is the difference between the desired share and the default share.

We use the mean and standard deviation of $AbsPercentGap_i$ from our pilot data to calculate the minimum detectable effect for our main study. The pilot study had a sample size of 29, with a mean $AbsPercentGap_i$ of 1.46 and a standard deviation of 0.90.

Our main study will employ an individually randomized design with a total sample size of 700, consisting of 350 participants each in the treatment and control groups, cross-randomized against the main treatment. Our MDE at 80% power is therefore 0.21SDs, which is equivalent to a 19 percentage-point difference in $AbsPercentGap_i$ or a 13% change.

<u>Consumption Outcomes for Inflation Treatment</u>

We will analyze the effect of the inflation treatment on consumption using the 350 households in the control group for the main study. Our sample size is therefore 175 observations per study arm.

We obtain statistics on household expenditure in Ghana from Agyepong et al. (2024), which use GLSS data from 2017. Poor households have a mean daily expenditure of 3.78 cedis with a standard deviation of 0.606 cedis, while ultra-poor households have a mean daily expenditure of 1.80 cedis with a standard deviation of 0.605 cedis. We can calculate a mean daily expenditure for poor households are 3.78 × 7= 26.46, for ultra-poor households are 1.80 × 7= 12.6

To estimate the standard deviation of household total expenditure over the past 7 days, we accounted for the correlation between daily expenditures. Assuming a daily expenditure correlation coefficient of 0.6 (reflecting the stability of household spending patterns and the persistence of income constraints), the standard deviation for 7-day expenditure is calculated as: √(7 + 42×0.6) × 0.606 = 3.44 cedis.

Under an experimental design with a sample size of 350 households, a significance level α=0.05, and statistical power of 80%, the minimum detectable effect (MDE) is again 0.29SDs, which is approximately 1 cedi worth of 7-day expenditure. Converting the MDE to relative effects, for poor households (with a mean 7-day expenditure of 26.46 cedis), the MDE corresponds to a 3.7% change in expenditure; for extremely poor households (with a mean 7-day expenditure of 12.6 cedis), the MDE corresponds to a 7.9% change in expenditure.

Based on findings from Coibion et al. (2023), each 1 percentage-point increase in inflation expectations leads to a 10% increase in non-durable goods spending. Considering the differences in our research environment, we expect a weaker effect, conservatively estimating that each 1 percentage point change in inflation expectations will lead to only a 0.5% change in expenditure. However, the key factor is that inflation expectations themselves exhibit substantial variability—household inflation expectations deviate from professional forecasts by an average of 45.5 percentage points. We assume that people will update their priors by half of this gap, consistent with other research on subjective expectations (e.g. Kerwin and Pandey 2025). Therefore, even with a small unit effect (0.5%), the overall effect remains substantial: 22.75 × 0.5% = an 11.4% change in expenditure, which exceeds even our more-conservative MDE threshold of 7.9%. This indicates that our research design has sufficient statistical power to detect the expected impact of inflation expectations on household expenditure.

References

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