What I Say Depends on How You Ask: Experimental Evidence of the Effect of Framing on the Measurement of Attitudes*

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Abstract

We use a survey experiment to document the presence of framing effects in measurement of attitudes. Using standard techniques for generating aggregate indices, we find that the framing of the underlying statements can meaningfully influence the relationship of the index with relevant covariates—in some cases changing the magnitude, statistical significance, and even the sign of the estimated relationship. We conclude by discussing how randomizing statement framing across respondents can help address bias in the measurement of attitudes.

Keywords: Survey design, attitudes, response bias, framing effects, non-classical measurement error, data collection

JEL Classification Codes: C83, D91, G41

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1 Introduction

We are often interested in quantitatively measuring attitudes within a population using a Likert scale (Likert, 1932). The framing of Likert scale statements could lead to differential responses due to, for example, social norms or desirability, a reluctance to report indifference, or a tendency to acquiesce. The standard approach, therefore, is to include both positively and negatively framed statements in the hope of mitigating bias (Dunsch, Evans, Macis and Wang, 2018). We use a survey experiment to (i) test for the presence of statement framing, (ii) document the consequences of framing effects when using measures of attitudes to construct an aggregate index with both positively and negatively framed statements, and (iii) proposing a solution to the problem.

While administering a survey module that measures attitudes toward mobile money, we randomly assign respondents into one of two groups. In the first group, which we call our control group for ease of exposition, we provide three positively framed statements and three negatively framed statements. In the second group, our treatment group, we also provide three positively framed statements and three negatively framed statements, but the framing is in the converse of the control group. Table 1 lists the statements received by each group.[1]

Table 1: Statement Framing

Treatment (N = 1,930)	Framing	**Control** (N = 2,001)	Framing
Mobile banking is not trustworthy	Negative	Mobile banking is trustworthy	Positive
Mobile banking is unsafe for saving money	Negative	Mobile banking is safe for saving money	Positive
Mobile banking is unsafe for transactions	Negative	Mobile banking is safe for transactions	Positive
Mobile banking is not too expensive	Positive	Mobile banking is too expensive	Negative
Mobile banking is easy to use	Positive	Mobile banking is hard to use	Negative
Mobile banking is for someone like me	Positive	Mobile banking is not for someone like me	Negative

Notes: We embed this survey experiment within the baseline survey of a study on digital financial services in Bangladesh (Rahman and Bloem, 2020).

2 Identifying Framing Effects and Possible Consequences

We directly test for framing effects using the following linear regression.

$$Y_i = \alpha + \beta Treatment_i + \epsilon_i \quad (1)$$

Y_i represents a binary variable indicating if the respondent chooses "completely agree" or "agree" to positively framed statements or "completely disagree" or "disagree" to negatively framed statements. The variable $Treatment_i$ represents the randomized treatment assignment for each respondent (as described in Table 1). The coefficient β represents the estimated effect of statement framing. ϵ_i is an error term. We use heteroskedasticity-robust standard errors (Abadie, Athey, Imbens and Wooldridge, 2023).

[1]Table A.1 in the Supplemental Appendix reports summary statistics about our sample and shows the balance of these variables between the treatment and the control groups.

We find evidence of the existence of framing effects across each of the six statements.[2] Table 2 shows that these effects range in magnitude from 21 percentage points ($p < 0.01$) in column (5) to 7 percentage points ($p < 0.01$) in column (4). Framing effects persist among both positively and negatively framed questions. In columns (1) through (3), we find that the treatment led respondents to be 14–18 percentage points ($p < 0.01$) less likely to indicate that mobile banking is trustworthy, safe for savings, or safe for transactions. In columns (4) through (6), we find that treatment led respondents to be 7–21 percentage points ($p < 0.01$) more likely to indicate that mobile banking is not too expensive, easy to use, or for a person like themselves.

Table 2: Framing Effects on Reported Attitudes

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group receives:	Negatively framed statements			Positively framed statements		
	Trust	Safe saving	Safe transactions	Not too expensive	Easy to use	For me
Treatment	-0.177***	-0.139***	-0.165***	0.067***	0.210***	0.088***
	(0.013)	(0.015)	(0.013)	(0.016)	(0.016)	(0.015)
Observations	3,931	3,931	3,931	3,931	3,931	3,931
R-squared	0.043	0.022	0.039	0.005	0.045	0.008

Notes: Robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1

We now demonstrate the possible consequences of bias due to framing effects using two standard techniques commonly used by applied quantitative researchers: (i) Kling index (Kling, Liebman and Katz, 2007) and (ii) principal component analysis (PCA). We then estimate the following linear regression:

$$Y_i = \gamma + \delta Treatment_i + \lambda Covariate_i + \theta(Treatment_i \times Covariate_i) + \eta_i \qquad (2)$$

Table 3 presents results from estimating variations on equation (2), and demonstrates the possible consequences of framing effects. In panel A of Table 3, we include a binary variable indicating if the respondent is the head of their household and interact this variable with our treatment variable. We find meaningful differences in the conditional mean of each aggregated index associated with being a household head between the treatment and control groups. In column (1), when using the Kling index, we find that although the sign of this observed difference is robust, the magnitude and statistical significance both meaningfully differ by treatment status. Additionally, a formal test of difference in these conditional means by treatment status shows that this observed difference is statistically significant. In column (2), when using the PCA index, the conditional means are statistically significant. Strikingly, we find that not only do the magnitude and statistical significance of these conditional means differ by treatment status, but sign differs as well.

In panel B of Table 3, we include a binary variable indicating if the respondent has completed

[2]Figure A.1 in the Supplemental Appendix shows the distribution of response in each category for each statement.

Table 3: Aggregated Index Analysis

	(1) Kling index	(2) PCA index
Panel A:		
Treatment	-0.134***	-0.455***
	(0.039)	(0.055)
Household head	-0.166***	-0.240***
	(0.045)	(0.061)
Treatment × Household head	0.079	0.072
	(0.068)	(0.098)
Constant	0.109***	0.292***
	(0.025)	(0.034)
Treatment = 1 & Household head = 1	-0.113***	-0.331***
Treatment = 0 & Household head = 1	-0.057	0.052
Difference (p-value)	0.018	0.031
Observations	3,931	3,931
R-squared	0.007	0.027
Panel B:		
Treatment	-0.087**	-0.425***
	(0.038)	(0.054)
Completed class 9	0.271***	0.203***
	(0.045)	(0.061)
Treatment × Completed class 9	-0.061	-0.004
	(0.070)	(0.100)
Constant	-0.022	0.155***
	(0.025)	(0.034)
Treatment = 1 & Completed class 9 = 1	0.101**	-0.071
Treatment = 0 & Completed class 9 = 1	0.249***	0.358***
Difference (p-value)	0.002	0.155
Observations	3,931	3,931
R-squared	0.014	0.027

Notes: Column (1) uses an aggregated index constructed using the technique of Kling et al. (2007). Column (2) uses an aggregated index constructed using principal component analysis. The "difference (p-value)" row in each panel tests the difference in the estimated conditional means in the preceding two rows. Robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1

class 9. In column (1), when using the Kling index, we find that the sign and statistical significance of this observed difference is robust. However, the magnitude differs by more than a factor of two and a formal test of difference in these conditional means by treatment status shows that this observed difference is statistically significant. In column (2), when using the PCA index, although the magnitude, statistical significance, and sign of these conditional means differ by treatment status, a formal test of difference in these conditional means by treatment status shows that this observed difference is not statistically significant. These results demonstrate that the consequences of framing effects on estimated conditional means of aggregated indices can vary by the technique used to construct the aggregated index, even when—following recommendations for mitigating acquiescence bias (Dunsch et al., 2018)—the index includes a mix of both positively and negatively framed statements.

3 Randomizing Statement Framing as a Solution

When all respondents to the survey receive statements framed in the same way, framing effects become a systematic feature of the data and cannot be accounted for in any analysis using the

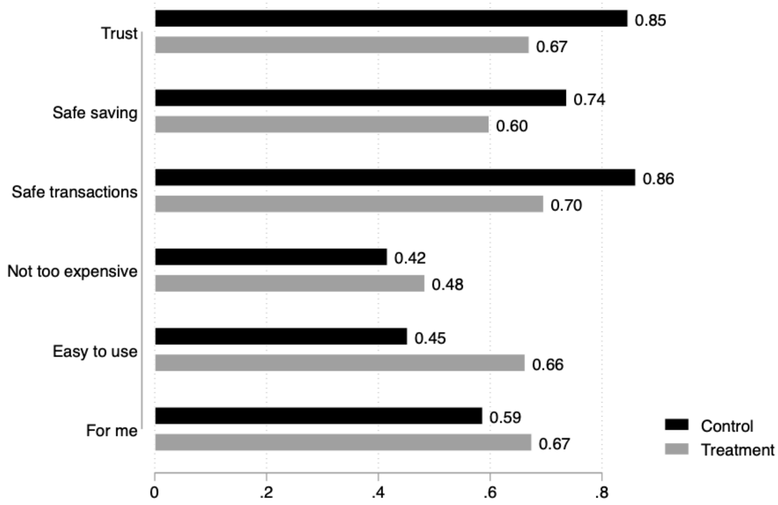

Figure 1: Bounded Estimates of Attitudes toward Mobile Banking
Notes: This figure shows bar graphs representing bounds on reported attitudes toward mobile banking.

survey data. To limit this systematic bias, we propose that future surveys randomize the framing of statements following this survey experiment.This approach makes statement framing independent from responses within the full sample and allows researchers to identify statement framing and account for it directly when analyzing the data.

In regression analysis, researchers can control from the randomly assigned statement framing group. Controlling for treatment assignment and interacting this variable with a covariate of interest allows the researcher to obtain two estimates of the relationship between a variable of interest and an attitude measure. Taken together these two estimates can be used as bounds on the correlation of interest. As shown in panels A and B in Table 3, relatively wide bounds—especially those that include zero—indicate that a particular relationship is relatively sensitive to the framing of the statements used to measure attitudes. Without the ability to directly account for statement framing, estimates from formal regression analysis will likely fall somewhere within the bounds estimated in Table 3 and the researcher will not have the ability to assess sensitivity of the magnitude, statistical significance, or sign to statement framing. Importantly, results and policy conclusions might be biased and the researcher will have no way of addressing this bias.

When estimating population parameters researchers can do so separately for both groups and present estimates as bounds on the true value of the parameter (akin to partial identification (Manski, 2003; Molinari, 2020; Tamer, 2010)). We demonstrate this approach in Figure 1, which reports the mean value of each of the binary variables used as the dependent variable in equation (1) for both the control and treatment groups. For example, we can credibly report that between 67 and 85 percent of our sample feel that mobile banking is trustworthy.

4 Conclusion

We directly estimate the effect of statement framing and demonstrate the possible consequences of framing effects by generating aggregate indices, using standard techniques, with a mix of both positively and negatively framed statements. We find instances where the framing of the underlying statements within the aggregated index meaningfully influences the magnitude, statistical significance, and often the sign of estimated correlations between these indices and relevant covariates. We also discuss how our experimental design combined with a bounding approach can help address the problem of framing effects biasing research conclusions and policy choices that are based on empirical analysis using quantitative measures of attitudes.

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Supplemental Appendix A

The Supplemental Appendix includes the following additional results.

- Figure A.1 plots histograms illustrating the percent of respondents indicating each response category.
- Table A.1 reports basic summary statistics about our sample and shows balance between the treatment and control groups.

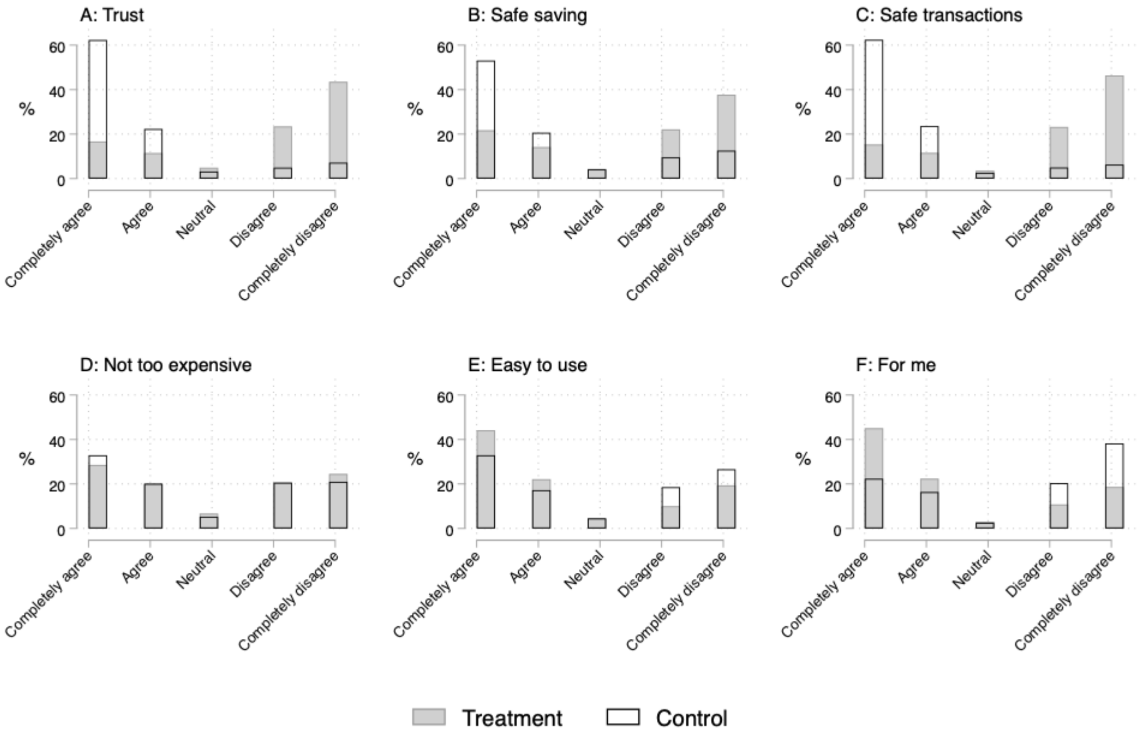

Figure A.1: Histograms of Responses by Treatment Group

Notes: This figure shows histograms reporting the percent of respondents reporting each of the response categories by treatment group.

Table A.1: Balance Table and Summary Statistics

	(1) Control		(2) Treatment		(1)-(2) Pairwise t-test	
	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference
Female (= 1)	2001	0.992 (0.002)	1930	0.993 (0.002)	3931	-0.001
Married (= 1)	2001	0.926 (0.006)	1930	0.925 (0.006)	3931	0.001
Household size	2001	4.763 (0.042)	1930	4.881 (0.046)	3931	-0.118*
Household head (= 1)	2001	0.337 (0.011)	1930	0.336 (0.011)	3931	0.002
Has mobile money account (= 1)	2001	0.475 (0.011)	1930	0.461 (0.011)	3931	0.015
Has bank account	2001	0.626 (0.011)	1930	0.589 (0.011)	3931	0.037**
Completed class 9 (= 1)	2001	0.276 (0.010)	1930	0.256 (0.010)	3931	0.020
Worked for pay (= 1)	2001	0.419 (0.011)	1930	0.413 (0.011)	3931	0.006
No job (= 1)	2001	0.510 (0.011)	1930	0.518 (0.011)	3931	-0.008
Has savings (= 1)	2001	0.951 (0.005)	1930	0.951 (0.005)	3931	-0.000
Receives remittances (= 1)	2001	0.372 (0.011)	1930	0.395 (0.011)	3931	-0.023
Has loans (= 1)	2001	0.863 (0.008)	1930	0.852 (0.008)	3931	0.011
Food expenditures	2001	11885.982 (134.928)	1930	12109.663 (134.908)	3931	-223.681
Education expenditure	2001	3224.529 (91.270)	1930	3169.913 (85.456)	3931	54.616
Health care expenditure	2001	2638.149 (70.183)	1930	2710.948 (63.997)	3931	-72.799
Household utilities expenditure	2001	2688.893 (55.295)	1930	2672.547 (52.659)	3931	16.346
Own a business	2001	0.102 (0.007)	1930	0.107 (0.007)	3931	-0.005

Notes: This table reports basic summary statistics and shows the balance in these statistics between the negative framing and positive framing groups. The expenditure figures report monthly expenditures at the household level. T-test uses robust standard errors. *** p<0.01, ** p<0.05, * p<0.1