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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 the measurement of attitudes. Next, using standard techniques for generating aggregate indices, we find that statement framing 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.

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 et al., 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) propose 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, our control group, we provide three positively framed statements and three negatively framed statements. In the second group, our treatment group, we provide the same statements, but the framing is the converse of the control group. Table 1 lists the statements received by each group.[1]

Our analysis reveals evidence of framing effects, which motivates mixing the framing of statements while designing surveys in an effort to mitigate framing effects when aggregating responses to survey questions measuring attitudes. Constructing a single variable from a battery of survey responses, we find that statement framing can change the magnitude, statistical significance, and sign of relationships between this single variable and relevant covariates.

2. Identifying framing effects and possible consequences

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

$$Y_i = \alpha + \beta Treatment_i + \epsilon_i \tag{1}$$

Y_i represents a binary variable indicating if the respondent chooses "completely agree" or "agree" to positively framed statements or

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[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.

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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).

Table 2
Framing effects on reported attitudes.

Treatment group receives:	(1) Negatively framed statements	(2)	(3)	(4) Positively framed statements	(5)	(6)
	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 ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

"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 et al., 2023).

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.

The results in Table 2 essentially follow Dunsch et al. (2018) and replicate the finding of framing effects in a different setting with a few subtle differences. Of note, Dunsch et al. (2018) implement a survey experiment randomly assigning respondents to one of three treatment groups: (i) receiving a questionnaire with all positively framed statements, (ii) receiving a questionnaire with all negatively framed statements, and (ii) receiving a questionnaire with a mix of positively and negatively framed statements.

We build on the findings of Dunsch et al. (2018) by demonstrating the possible consequences of bias due to framing effects using two standard techniques commonly used by applied quantitative researchers to aggregate multiple responses into a single variable: (i) Kling index (Kling et al., 2007) and (ii) principal component analysis (PCA). Specifically, we estimate the following linear regression:

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

Y_i is either a Kling index or a PCA index aggregating each of the binary variables used as dependent variables in Table 2 into a single variable. $Treatment_i$ is defined as above under Eq. (1) and $Covariate_i$ is defined as either a binary variable indicating if the respondent is the head of their household or has completed class 9, as detailed below. η_i is an error term.

[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)
Conditional mean:		
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)
Conditional mean:		
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 ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3 presents results from estimating variations on Eq. (2). 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

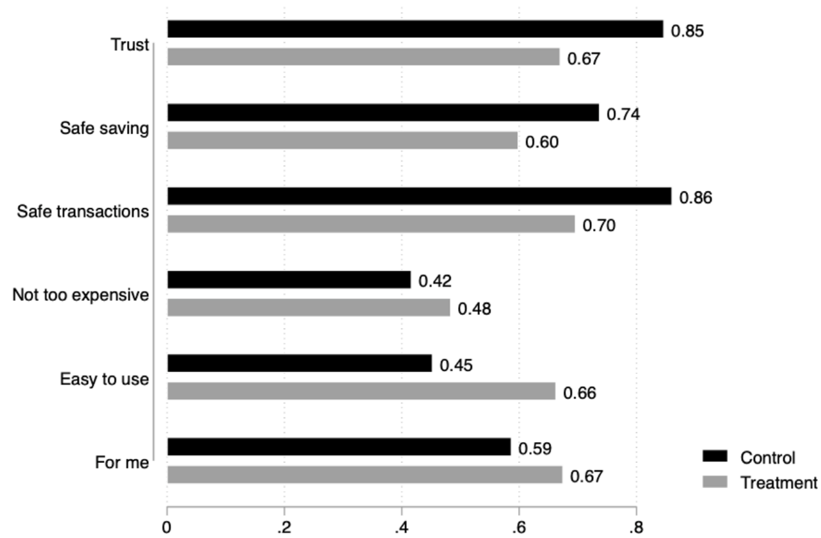

Fig. 1. Bounded Estimates of Attitudes toward Mobile Banking. *Notes*: This figure shows bar graphs representing bounds on reported attitudes toward mobile banking.

household head between the treatment and control groups.[3] In column (1), when using the Kling index, we find that although the sign of the conditional means are 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, 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 class 9. In column (1), when using the Kling index, we find that the sign and statistical significance of these conditional means are robust. However, the magnitude differs meaningfully and 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, this observed difference is not statistically significant.

These results demonstrate the consequences of framing effects on estimated conditional means of aggregated indices, even when – following recommendations for mitigating acquiescence bias (Dunsch et al., 2018) – the index includes a mix of both positively and negatively framed statements. Most strikingly, not only do we find that framing effects can meaningfully change the magnitude and statistical significance of estimated relationships, but the sign of these relationships can also change.

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 survey data. To limit this systematic bias, we propose that future surveys randomize the framing of statements across respondents.

In regression analysis, researchers can control for the randomly assigned statement framing. 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.

When estimating population parameters researchers can do so separately for both groups and present estimates as bounds on the true value of the parameter. We demonstrate this approach in Fig. 1, which reports the mean value of each of the binary variables used as the dependent variable in Eq. (1) for both the control and treatment groups.

Without the ability to directly account for statement framing, estimates from formal regression analysis or the estimation of population parameters might be biased and the researcher will have no way of addressing this bias. Randomizing statement framing across respondents allows researchers to credibly estimate bounds, an approach akin to partial identification (Manski, 2003; Molinari, 2020; Tamer, 2010).

4. Conclusion

Following Dunsch et al. (2018), we directly estimate the effect of statement framing. Building on these results, and extending the work of Dunsch et al. (2018), we additionally 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 the sign of estimated relationships between these indices and relevant covariates. Furthermore, we 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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2024.111686.

[3] With a binary covariate the conditional mean of the index when $Treatment_i = 1$ and $Covariate_i = 1$ is the sum of $\gamma + \delta + \lambda + \theta$ in Eq. (2) and the conditional mean of the index when $Treatment_i = 0$ and $Covariate_i = 1$ is the sum of $\gamma + \lambda$ in Eq. (2).

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