Financial Conduct Authority

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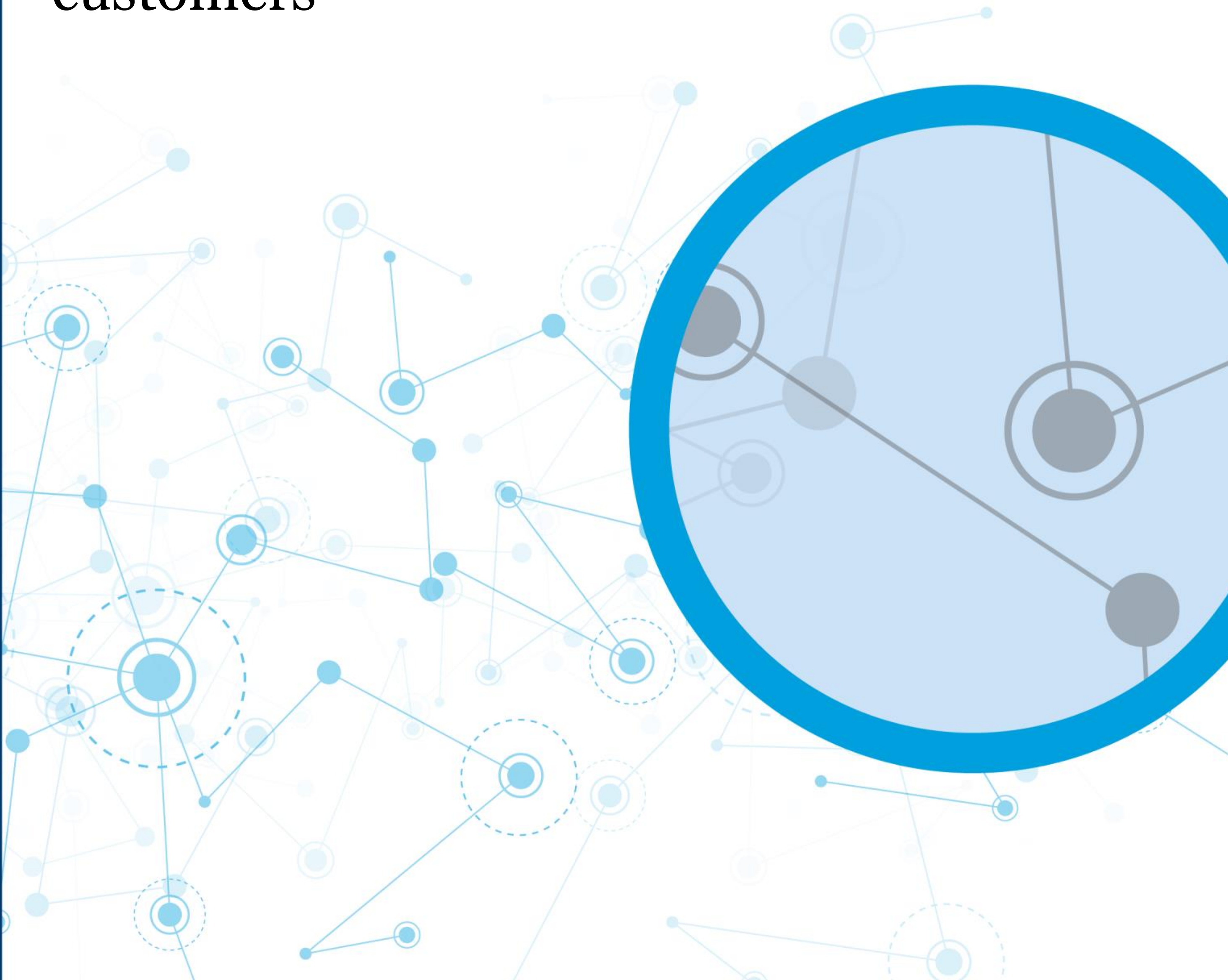
Occasional Paper 65: Annex 3

11 September 2024

Annex 3. Is timing of the essence? Testing when to engage UK pension customers



Contents

Experiment 1: literature review & methodology

Section 1: Impact of subject lines on open rates literature review

Personalisation of email subject lines:

Sahni & Chintagunta (2016) found that adding the name of the message recipient to the email's subject-line increased the probability of the recipient opening it by 20% (from 9.05% to 10.80%).

- 68,088 email-ids were randomized into the following two groups, where the only difference between the emails received by the treatment and control group was that the subject line mentioned the recipient's name in the treatment but not the control group.
- Context: collaboration with three companies selling a diverse set of products (commercial)

Scott *et al.* (2022)

- Found that recipients of emails personalised with the legislator's name were **51% more likely to open** and opened 37% more times than recipients of non-personalised emails (no baselines provided).
- Context: increasing the reach of science to legislators (political)

Stupar-Rutenfrans *et al.* (2019)

- A/B test was conducted where an email marketing message sent to a total of 1,409,963 customers of bol.com
- The found that the control group had an open rate of 24.3%, the personal subject line 25.0%, **so an increase of 0.7 pp (29%)**, the short subject line 26.9% and the emotion inducing subject line 26.1%
- The personalised subject line contained the first name of the customer
- Context: marketing emails for bol.com (commercial)

Calfano (2016)

- Finds **that personalised subject lines do not appear to have an advantage** over their non-personalised counterparts for open rates
- Context: sending emails from Planned Parenthood (n ~ 82,000)

Behavioural framing:

Martin *et al.* (2022) Behavioural framing of incentives in subject line and email content:

- Hypotheses were that email communications which utilised the endowment effect, social proof or altruism would lead to higher conversion rates than messages regarding incentivisation, but analysis led to a rejection of all hypotheses
- **None of the tested framing effects performed significantly better**, as per chi-squared tests, than the financial incentive group across open rate, click rate, conversion rate or engagement rate
- Context: 91,289 recruitment emails delivered to Aegon customers across various weekday mornings

Miller *et al.* (2020)

- Trialled 'action instruction' subject lines against 'action instruction' plus gain frames and against 'non-loss' frames
- Found that emails with the Action Instruction only subject line were more likely to be opened; there was **no difference in open rate between the two framed subject lines**, and no effect on click-through rates
- Context: Students (N = 38,538) at a Midwestern university received emails from their health clinic about a stress management program

Maltz *et al.*(2022)

- **No effect of message framing on uptake rates was observed**
- Frames included: gains, losses, doctor recommendation, implementation intentions and empowerment
- Report two secondary suggestive findings:
    - (1) shorter subject lines are positively correlated with opening rates, and
    - (2) emails seem to outperform text messages in terms of overall success rates
- Context: large scale field study (n = 113, 048) where health service invited members aged 50-74, via email or as a text message, to take preventive medical actions that are recommended for them by the ministry of health

Other subject line characteristics:

Kumar (2021):

- Finds that longer subject line length (-0.05, $p \leq .01$) and larger email size (-0.22, $p \leq .01$) reduce the likelihood of email opening

Section 2: Analytical strategy for Experiment 1

Sample Size and Power Calculations

We corrected for multiple comparisons among the primary outcomes using the Bonferroni correction. For the stage one primary outcome, there was one control email subject line and four treatment subject lines, resulting in 10 pairwise comparisons. For the stage two primary outcome, there was one control email and four treatment emails, again resulting in 10 pairwise comparisons. This gave us a total of 20 comparisons for the primary analysis.

We conducted t-tests of proportions to assess the statistical significance of differences. Assuming a significance level of 95% and adjusting for multiple comparisons using the Bonferroni correction, we used an alpha of 0.0025.

To calculate the effect size, we used a baseline email open rate of 65% and set the minimum detectable effect at 5 percentage points. The parameters for the power calculations were as follows:

- Power = 0.8
- Alpha = 0.05/20 = 0.0025
- Cohen's H = 0.1
- Two-sided test

This resulted in a minimum required sample size of 3,000 per trial arm. With five trial arms, the total required sample size for experiment 1 was 15,000.

Assuming an estimated click-rate baseline of 10%, we were powered to detect a difference of 3 percentage points. We could detect smaller effects if the control group had a smaller click-through rate. For example, if the control group's click-through rate was 5%, we could detect a 2.4 percentage point difference.

Our population of interest was UK adults aged 22-26. To obtain this sample, we set the following filters in Prolific:

1. Age – 22-66
2. Country – United Kingdom

Statistical Models and Comparisons

We used a linear probability model to estimate the impact of treatment assignment on the likelihood of clicking on the pension email subject line (SL). We conducted the following 10 comparisons:

- SL T1 against SL Control
- SL T2 against SL Control
- SL T3 against SL Control
- SL T4 against SL Control
- SL T2 against SL T1
- SL T3 against SL T1
- SL T4 against SL T1
- SL T3 against SL T2
- SL T4 against SL T2
- SL T4 against SL T3

The model specification was:

$$Y_i = \beta_0 + \beta_{1-4} SL_i + \omega_i$$

Where:

- Y_i is a binary variable, coded 1 when the pension email subject line was clicked on and coded 0 when it was not clicked on (or in the case of attrition).
- SL_i is a matrix of four subject line treatment allocation dummies (one for each treatment group apart from the control).
- β_{1-4} are the coefficients of interest, estimating the treatment effects.
- ω_i are Huber White robust standard errors.

We also included a matrix of covariates X_i:

- Gender dummies: Female (base group), Male, Non-Binary or “Prefer not to say” (combined).
- Age group dummies: 22-29 (base group), 30-39, 40-49, 50-66.
- Household income dummies: less than £15,999 (base group), £16,000-29,999, £30,000-49,999, £50,000-69,999, £70,000-99,999, £100,000-149,999, more than £150,000, prefer not to say.

  This model specification was:

$$Y_i = \beta_0 + \beta_1 SL_i + \beta_2 X_i + \omega_i$$

We added covariates to increase statistical power, not to interpret their coefficients. Given that open rates were around 50-60%, a linear probability model was deemed adequate. However, if any of the following conditions applied, we ran a logistic regression instead:

- The OLS confidence intervals lay outside 0 or 1.
- The OLS confidence intervals lay closer to 0 or 1 than the estimated parameter.
- The proportion of the outcome in the control group was less than 5% or more than 95%.

The main model reported was the OLS model with covariates. If significant differences arose from logistic regression or between models with or without covariates, further sensitivity analyses were conducted and reported accordingly.

Primary 2: Call-to-Action Click-Through Rate

For Primary 2, we used a logistic regression model to estimate the impact of treatment assignment on the likelihood of clicking on the pension email call-to-action, regardless of whether participants clicked on one of the pension subject lines. We conducted the following 10 comparisons:

- EC T1 against EC Control
- EC T2 against EC Control
- EC T3 against EC Control
- EC T4 against EC Control
- EC T2 against EC T1
- EC T3 against EC T1
- EC T4 against EC T1
- EC T3 against EC T2
- EC T4 against EC T2
- EC T4 against EC T3

We chose logistic regression for this analysis due to the expected low proportion of participants clicking the CTA, with an expected rate of around 5-6%. The model specification was:

$$\log\left(\frac{p}{1-p}\right)_i = \beta_0 + \beta_{1-4}SL_i + \beta_{5-8}EC_i + \beta_{9-33}SL_iEC_i + e_i$$

Where:

- p is the probability that our outcome binary variable is coded 1 (coded as 1 when the call-to-action in the pension email was clicked on and 0 when it was not clicked on. Participants who do not open the pension email, and therefore cannot click the call-to-action, and drop-outs, are also coded as 0).
- SL_i is a matrix of four subject line treatment allocation dummies (one for each treatment group apart from the control). In this case, these dummies are simply used as controls, rather than to interpret the coefficients.
- EC_i is a matrix of four email content treatment allocation dummies (one for each treatment group apart from the control). β_{5-8} are the coefficients of interest, estimating the treatment effects.
- SL_iEC_i is a matrix of 25 different interactions amongst subject line and email content treatments. We will not interpret the interaction effects and hypothesise there not to be any, but include them as nuisance parameters to avoid distortion.
- e_i are standard errors.

We included the same matrix of covariates X_i to increase statistical power.

Sensitivity Analysis of Primary 2

We ran the Primary 2 model with and without interaction terms and conducted an F-test to compare the models. If the interactions did not significantly affect the model, we interpreted the results as described. Significant differences indicated interaction effects, which we explored for further insights, although not powered to interpret individual effects.

Secondary 1: Click-Through Rate of Those Who Opened the Email

For Secondary 1, we ran the same specification as for Primary 2, with the outcome measure coded differently (excluding participants who did not open the email). We expected similar findings to Primary 1, with the analysis rebasing results to those who opened the email.

Exploratory Analysis: Subgroup Analysis

We conducted exploratory subgroup analysis by running primary analysis regressions for different subgroups:

- Gender: Female, Male, Non-Binary/Prefer not to say.
- Age groups: 22-29, 30-39, 40-49, 50-66.

For each subgroup, we used a model with an interaction between treatment and subgroup indicators, focusing on treatment coefficients rather than interaction terms. This approach aimed to identify treatment effects within each subgroup, with appropriate caveats due to limited power for detecting significant differences between subgroups.

Experiment 1: results

Table 1: Primary Outcome 1 Results, Experiment 1

	Effect of subject line treatment on proportion of respondents opening the email	
	Primary Outcome 1	
	(1)	(2)
Few more steps	0.092*** (0.012)	0.094*** (0.012)
Future you	0.114*** (0.012)	0.113*** (0.012)
Key Questions	0.021 (0.013)	0.020 (0.013)
Take income	0.032* (0.013)	0.031* (0.013)
Gender: Male		-0.015 (0.008)
£16,000-29,999		0.032* (0.016)
£30,000-49,999		0.051*** (0.015)
£50,000-69,999		0.051** (0.016)
£70,000-99,999		0.071*** (0.018)
£100,000-149,999		0.037 (0.025)
More than £150,000		0.059 (0.044)
PNTS		0.012 (0.018)
Age: 30-39		-0.001 (0.010)
Age: 40-49		0.016 (0.012)
Age: 50-66		0.063*** (0.012)
Observations	15,098	14,985
R^2	0.008	0.013
Adjusted R^2	0.008	0.012
Residual Std. Error	0.481 (df = 15093)	0.480 (df = 14969)
F Statistic	30.904*** (df = 4; 15093)	12.767*** (df = 15; 14969)
Note:		*p<0.05; **p<0.01; ***p<0.001
		Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.
		Constants are not displayed as there are no AMEs associated with them.
		Model 1 displays the results of just the independent variables impact on the outcome.
		Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Table 2: Primary Outcome 2 Results, Experiment 1

	Effect of treatment on likelihood of click through rate	
	Primary Outcome 2	
	(1)	(2)
Headstart Framing	0.008 (0.009)	0.006 (0.009)
Present Bias	-0.004 (0.009)	-0.004 (0.009)
Social Norms	0.006 (0.009)	0.004 (0.009)
Specific Questions	0.018 (0.009)	0.017 (0.010)
Few more steps	0.025** (0.009)	0.026** (0.009)
Future you	0.025** (0.009)	0.025** (0.009)
Key Questions	0.020* (0.009)	0.021* (0.009)
Take income	0.015 (0.009)	0.015 (0.009)
Gender: Male		0.003 (0.006)
£16,000-29,999		-0.014 (0.011)
£30,000-49,999		0.007 (0.011)
£50,000-69,999		0.011 (0.012)
£70,000-99,999		0.005 (0.014)
£100,000-149,999		-0.028 (0.018)
More than £150,000		0.018 (0.035)
PNTS		-0.010 (0.013)
Age: 30-39		-0.007 (0.007)
Age: 40-49		0.019* (0.009)
Age: 50-66		0.072*** (0.009)
Observations	15,098	14,985
Log Likelihood	-6,564.063	-6,471.635
Akaike Inf. Crit.	13,178.130	13,015.270
Note:		*p<0.05; **p<0.01; ***p<0.001
		Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.
		Constants are not displayed as there are no AMEs associated with them.
		Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Table 3: Secondary Outcome 1 Results, Experiment 1

	Call-to-action click-through rate, only of those who opened email	
	Secondary Outcome 1	
	(1)	(2)
Headstart Framing	0.015 (0.014)	0.013 (0.014)
Present Bias	-0.007 (0.014)	-0.006 (0.014)
Social Norms	0.002 (0.014)	-0.0002 (0.014)
Specific Questions	0.025 (0.014)	0.026 (0.014)
Gender: Male	0.003 (0.014)	
£16,000-29,999	-0.004 (0.014)	
£30,000-49,999	0.025 (0.015)	
£50,000-69,999	0.011 (0.014)	
£70,000-99,999		0.011 (0.009)
£100,000-149,999		-0.035 (0.018)
More than £150,000		-0.011 (0.017)
PNTS		-0.002 (0.019)
Age: 30-39		-0.020 (0.021)
Age: 40-49		-0.061^{*} (0.027)
Age: 50-66		0.004 (0.051)
incomePNTS		-0.020 (0.021)
agegroup30-39		-0.011 (0.011)
agegroup40-49		0.025 (0.013)
agegroup50-66		0.084^{***} (0.014)
Observations	9,494	9,460
Log Likelihood	-5,332.124	-5,281.188
Akaike Inf. Crit.	10,714.250	10,594.380

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.

Constants are not displayed as there are no AMEs associated with them.

Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Experiment 1 & 2: treatments

Figure 1. Experiment 1 & 2 - Control Email

Find out about your retirement options

Dear member,

When the time comes to retire, you'll have to make an important decision about how to take the money from your pension. Understanding the options available to you will help you make an informed decision, and can help you plan for retirement.

You don't need to go it alone, you can use the government's MoneyHelper service for free and impartial guidance on pensions. Go to MoneyHelper.

What's MoneyHelper?
- MoneyHelper is a service backed by government, offering free, impartial guidance on how to take your pension.
- They'll explain how your options for taking your savings work and the other things you need to think about when planning for your retirement.

Take me to MoneyHelper

Kind regards,
The MyPension Team

Figure 2. Experiment 1 & 2 - Treatment Email:

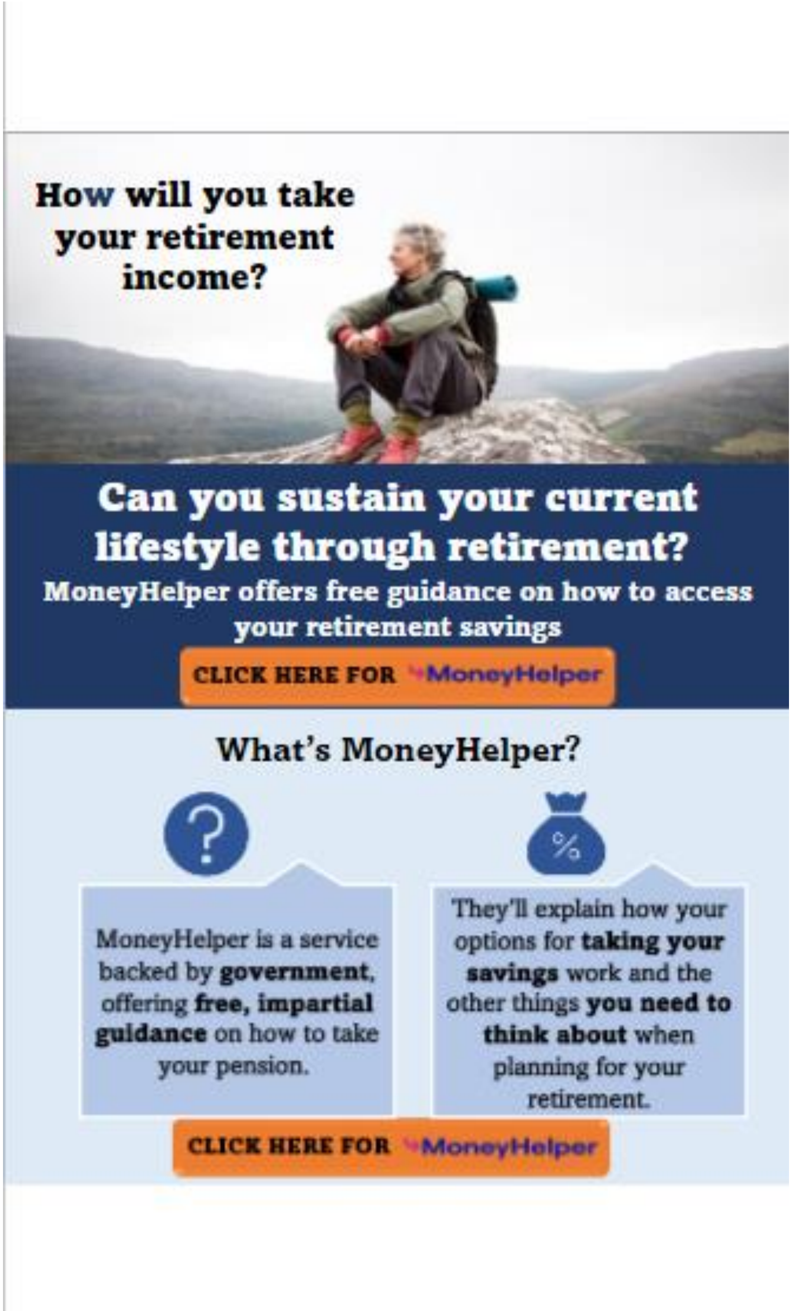


Figure 3. Experiment 1 & 2 - Treatment Email:

Figure 4. Experiment 1& 2 - Treatment Email:

Figure 5. Experiment 1 & 2 - Treatment Email:

Experiments 2 & 3: methodology

Section 3: Analytical Strategy for Experiment 2 & 3

Sample Size and Power Calculations

We corrected for multiple comparisons within the primary outcomes in Experiment 2/3 using the Bonferroni correction. For the primary analysis, we compared treatment arms to the control but not between each other, resulting in 8 comparisons to correct for.

We conducted t-tests of proportions to assess the statistical significance of differences. Assuming a significance level of 95% and adjusting for multiple comparisons using the Bonferroni correction, the parameters for the power calculations to detect small effect sizes were as follows:

- Power = 0.8
- Alpha = 0.05/8 = 0.00625
- Cohen's H = 0.2
- Two-sided test

This provided a minimum sample size of 560 participants per trial arm. However, we had resource for 800 participants per trial arm after accounting for the sample from Experiment 1 and considering we had 5 trial arms. Using 800 participants increased our power slightly.

Assuming a baseline awareness of a decumulation decision at 73% from the 2022 Financial Lives Survey results, a sample of 800 per trial arm gave us the power to detect a change of 7.5 percentage points above the control arm.

For the second primary outcome, we tested if the mean attitude score for MoneyHelper was significantly greater in the treatment arms compared to the control arm. Possible scores ranged from 0 to 4, and with our sample size, we could detect differences in means equivalent to a Cohen's D of 0.17, indicating relatively small mean differences.

Sample Requirements

Our population of interest comprised UK adults aged 22-66. To obtain this sample, we set the following filters in Prolific:

- Age: 22-66
- Country: United Kingdom

Primary 1: Awareness of Decumulation Decision

We ran an OLS regression to estimate the impact of treatment assignment on the likelihood of correctly selecting the multiple-choice option on question 1, indicating that a decumulation decision must be made (option b, coded as 1 if the individual selected option b, or 0 if they selected other options or did not select anything, indicating attrition).

The model specification was:

$$Y_i = \beta_0 + \beta_1 T_i + \omega_i$$

Where:

- Y is a binary variable (coded as explained above)
- T_i is a matrix of four treatment allocation dummies (one for each treatment group apart from the control).
- ω_i are Huber White robust standard errors.

We also ran the same specification including a matrix of covariates X_i:

- Gender dummies: Female (base group), Male, and Non-Binary or "Prefer not to say" (combined).
- Age group dummies: 22-29 (base group), 30-39, 40-49, 50-66.
- Household income dummies: less than £15,999 (base group), £16,000-29,999, £30,000-49,999, £50,000-69,999, £70,000-99,999, £100,000-149,999, more than £150,000, prefer not to say.

  The model specification was:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + \omega_i$$

We included the covariates to increase statistical power, not to interpret their coefficients.

Primary 2: Attitude Toward MoneyHelper Composite Score

We ran a quasi-binomial regression to estimate the impact of treatment assignment on the Attitudinal Composite Score (ACS), reflecting how positively participants responded to survey questions 3-6 about MoneyHelper. The score was based on 4 outcomes and was coded by counting each of the 4 outcomes. The outcomes were as follows:

1) Use of MoneyHelper service ever
2) Use of MoneyHelper service in the next 12 months
3) Think MoneyHelper service is helpful
4) Trust MoneyHelper service

We made the following 10 comparisons:

- Control against Email Treatment 1
- Control against Email Treatment 2
- Control against Email Treatment 3
- Control against Email Treatment 4
- Email Treatment 1 against Email Treatment 2
- Email Treatment 1 against Email Treatment 3
- Email Treatment 1 against Email Treatment 4
- Email Treatment 2 against Email Treatment 3
- Email Treatment 2 against Email Treatment 4
- Email Treatment 3 against Email Treatment 4

The model specification was:

$$Y_i \sim quasibinomial(n, pi, \phi)\ ;\ logit(p_i) = \alpha + \beta_T T_i + \beta_X X_i$$
$$var(Y_i) = n\phi p_i(1 - p_i)$$

Where:

- Y_i is a two-column integer matrix: the first column gives the number of attitudinal outcomes coded as 1 (out of 4), and the second column the number coded as 0 (as specified above); and

- T_i is a matrix of two treatment allocation dummies (one for each treatment group apart from the control).

We also ran the same specification with the same matrix of covariates as used above.

Secondary 1: Comprehension of MoneyHelper Service

We ran an OLS regression to estimate the impact of treatment assignment on the likelihood of correctly selecting the multiple-choice option on question 2, indicating comprehension of what MoneyHelper is (option a, coded as 1 if the individual selected option a, or 0 if they selected other options or did not select anything, indicating attrition).

The model specification was:

$$Y_i = \beta_0 + \beta_1 T_i + \omega_i$$

Where:

- Y is a binary variable (coded as explained above)
- T_i is a matrix of four treatment allocation dummies (one for each treatment group apart from the control).
- ω_i are Huber White robust standard errors.

We also ran the same specification including the same matrix of covariates as explained above. We included covariates to increase statistical power, not to interpret their coefficients.

Secondary 2-5: Attitudes Toward MoneyHelper

For each attitudinal outcome captured in our survey, we ran an OLS regression. If the conditions outlined above were violated, we ran a logistic regression. The regression estimated the impact of treatment assignment on the likelihood of reporting one of the following attitudes toward receiving guidance:

- Likelihood of ever using MH website, coded 1 if response was 'd. I probably will use the MoneyHelper website at some point' or 'e. I definitely will use the MoneyHelper website at some point', 0 otherwise (or in case of attrition).
- Likelihood of using MH website in the next 12 months, coded 1 if response was 'd. I probably will use the MoneyHelper website at some point' or 'e. I definitely will use the MoneyHelper website at some point', 0 otherwise (or in case of attrition).
- Perceived helpfulness of MH, coded 1 if response was 'd. Somewhat helpful' or 'e. Very helpful', 0 otherwise (or in case of attrition).
- Trust in information from MH, coded 1 if response was 'd. I would slightly trust it' or 'e. I would strongly trust it', 0 otherwise (or in case of attrition).

The model specification was:

$$Y_i = \beta_0 + \beta_1 T_i + \omega_i$$

Where:

- Y is a binary variable (coded as explained above)
- T_i is a matrix of four treatment allocation dummies (one for each treatment group apart from the control).
- ω_i are Huber White robust standard errors.

We also ran the same specifications including the same matrix of covariates as used above. Again, we expected these covariates to be approximately balanced across treatment groups, and included them to increase statistical power, not to interpret their coefficients.

Exploratory 1-5: Reasons for Not Using MoneyHelper Service

For each of these outcomes, we ran a logistic regression, anticipating that the conditions outlined above might be violated due to low proportions of the sample reporting certain barriers. The regression estimated the impact of treatment assignment on the likelihood of reporting one of the following barriers to receiving guidance:

- Trust, coded 1 if participant selected one or more of the following for question 7:
    - The information would be biased AND/OR
    - I wouldn't trust the information.
- Information avoidance/overload, coded 1 if participant selected one or more of the following for question 7:
    - Pensions are so complicated, I'd prefer not to think about them at all AND/OR
    - The information would be too complicated.
- Ease of access to information, coded 1 if participant selected one or more of the following for question 7:
    - It would take too much time AND/OR
    - It's too difficult to use the website.
- Confidence in own ability, coded 1 if participant selected one or more of the following for question 7:
    - The guidance would be too general or too simple AND/OR
    - I am informed enough already.
- Misconceptions about price, coded 1 if participant selected the following for question 7:
    - It would be too expensive.

The model specification was:

$$Y_i = \beta_0 + \beta_1 T_i + \omega_i$$

Where:
- Y is a binary variable (coded as explained above)
- T_i is a matrix of four treatment allocation dummies (one for each treatment group apart from the control).
- ω_i are Huber White robust standard errors.

We also ran the same specifications including the same matrix of covariates as used above. Again, we expected these covariates to be approximately balanced across treatment groups, and included them to increase statistical power, not to interpret their coefficients.

Exploratory 7-8: Sub-group Analysis

Although not properly powered to detect significant differences between sub-groups, we ran the primary analysis regressions, separating into different subgroups. For each of these, we used a model with an interaction between treatment and sub-group indicators, though we did not focus on the interaction term. Rather, we looked at the treatment coefficients (not on the interaction) when the reference group was taken to be each of the categories of the subgroup variable.The subgroup variables were:

- Gender (categorical variable defined in covariates section).
- Age groups (categorical variable defined in covariates section).
- Household income (categorical variable defined in covariates section).

We were not looking to estimate the size of the difference between the groups and were not powered to do so. However, we may still report the findings (including interaction terms) with appropriate caveats. Our aim was to calculate whether there was an effect for the given group.

Experiment 3: treatments

Figure 6. Experiment 3 – Present bias treatment email

Dear member,

When the time comes to retire, you'll have to make an important decision about how to take the money from your pension. Your pension is designed to cover the everyday needs that your income does now. The future you will thank you for taking simple steps now to understand the options available to you, so you can maintain your current lifestyle.

MoneyHelper offers free and impartial guidance on how to access your retirement savings. This will help you to make an informed decision, and can help you plan for retirement.

What's MoneyHelper?

- MoneyHelper is a service backed by government, offering free, impartial guidance on how to take your pension.
- They'll explain how your options for taking your savings work and the other things you need to think about when planning for your retirement.

Take me to MoneyHelper

Kind regards,
The MyPension Team

Figure 7: Experiment 3 – Specific questions treatment email

Dear member,

When the time comes to retire, you'll have to make an important decision about how to take the money from your pension. Thinking about retirement can be difficult. You may not feel as prepared as you'd like, and that's okay. Breaking it down into simple, key questions can help. Understanding the options available to you will support you to make an informed decision and to plan for retirement.

You don't need to go it alone, you can use the government's MoneyHelper service for free and impartial guidance on pensions. Go to MoneyHelper.

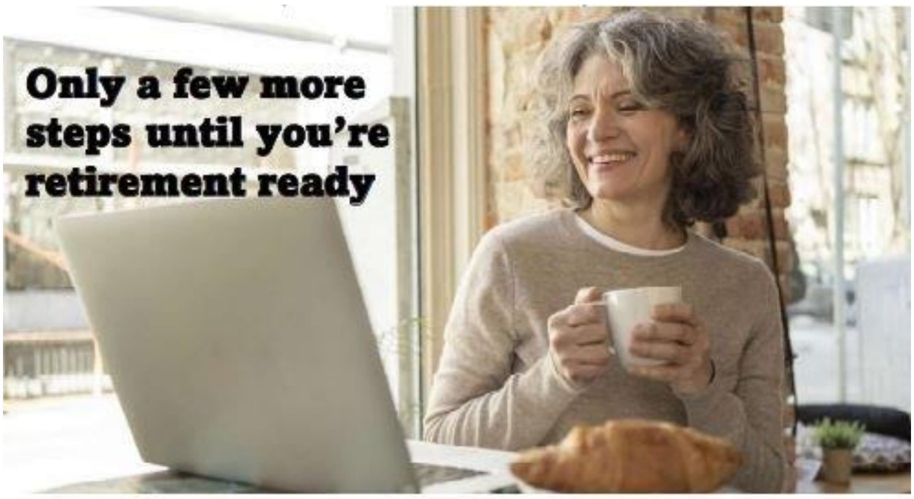
What's MoneyHelper?

- MoneyHelper is a service backed by government, offering free, impartial guidance on how to take your pension.
- They'll explain how your options for taking your savings work and the other things you need to think about when planning for your retirement.

Take me to MoneyHelper

Kind regards,
The MyPension Team

Figure 8. Experiment 3 – Head start treatment email



Dear member,

When the time comes to retire, you'll have to make an important decision about how to take the money from your pension. You've already made a great start, and there's just a few more steps you need to take:

- ✓ Start saving for retirement
- ✓ Think about what your retirement might look like
- ❑ Find out about your options from MoneyHelper
- ❑ Be ready to make an informed decision about retirement

What's MoneyHelper?

- MoneyHelper is a service backed by government, offering free, impartial guidance on how to take your pension.
- They'll explain how your options for taking your savings work and the other things you need to think about when planning for your retirement.

Take me to **MoneyHelper**

Kind regards,
The MyPension Team

Figure 9. Experiment 3 – Social norms treatment email

Dear member,

When the time comes to retire, you'll have to make an important decision about how to take the money from your pension. It's normal to feel unsure and most people seek help on what to do next. Understanding the options available to you will help you make an informed decision, and can help you plan for retirement.

You don't need to go it alone, you can use the government's MoneyHelper service for free and impartial guidance on pensions. Go to MoneyHelper.

What's MoneyHelper?

- MoneyHelper is a service backed by government, offering free, impartial guidance on how to take your pension.
- They'll explain how your options for taking your savings work and the other things you need to think about when planning for your retirement.

Take me to MoneyHelper

Kind regards,
The MyPension Team

Experiments 2 & 3: results

Table 4. Primary Outcome 1 Results, Experiment 2

	Effect of treatment on likelihood of correctly answering question around awareness of decumulation decision	
	Primary Outcome 1	
	(1)	(2)
Headstart Framing	-0.155*** (0.022)	-0.146*** (0.022)
Present Bias	-0.183*** (0.022)	-0.180*** (0.022)
Social Norms	-0.198*** (0.022)	-0.197*** (0.022)
Specific Questions	-0.197*** (0.022)	-0.196*** (0.022)
Gender: Male		-0.016 (0.015)
Age: 30-39		0.028 (0.020)
Age: 40-49		0.094*** (0.022)
Age: 50-66		0.165*** (0.022)
£16,000-29,999		0.045 (0.030)
£30,000-49,999		0.096*** (0.029)
£50,000-69,999		0.110*** (0.030)
£70,000-99,999		0.125*** (0.034)
£100,000-149,999		0.096* (0.048)
More than £150,000		0.183* (0.073)
PNTS		0.031 (0.034)
Observations	3,997	3,996
R^2	0.025	0.048
Adjusted R^2	0.024	0.045
Residual Std. Error	0.467 (df = 3992)	0.462 (df = 3980)
F Statistic	25.925*** (df = 4; 3992)	13.434*** (df = 15; 3980)
Note:		*p<0.05; **p<0.01; ***p<0.001
		Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.
		Constants are not displayed as there are no AMEs associated with them.
		Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Table 5. Primary Outcome 2 Results, Experiment 2

	Effect of treatment on Composite Score of Attitude Toward MoneyHelper	
	Primary Outcome 2	
	(1)	(2)
Headstart Framing	-0.073*** (0.014)	-0.069*** (0.014)
Present Bias	-0.066*** (0.014)	-0.064*** (0.014)
Social Norms	-0.050*** (0.014)	-0.049*** (0.014)
Specific Questions	-0.041** (0.014)	-0.042** (0.014)
Gender: Male		-0.052*** (0.009)
Age: 30-39		0.021 (0.012)
Age: 40-49		0.042** (0.013)
Age: 50-66		0.034* (0.014)
£16,000-29,999		0.030 (0.019)
£30,000-49,999		0.073*** (0.017)
£50,000-69,999		0.084*** (0.019)
£70,000-99,999		0.082*** (0.021)
£100,000-149,999		0.040 (0.031)
More than £150,000		0.072 (0.059)
PNTS		-0.011 (0.021)
Observations	3,997	3,996

Note: *p<0.05; **p<0.01; ***p<0.001

Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.

Constants are not displayed as there are no AMEs associated with them.

Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Table 6. Primary Outcome 1 Results, Experiment 3

	Effect of treatment on likelihood of correctly answering question around awareness of decumulation decision	
	Primary Outcome 1	
	(1)	(2)
Headstart Framing	-0.008 (0.019)	-0.009 (0.019)
Present Bias	-0.064** (0.020)	-0.064** (0.020)
Social Norms	-0.014 (0.020)	-0.016 (0.019)
Specific Questions	-0.068*** (0.021)	-0.071*** (0.020)
Gender: Male		-0.136*** (0.025)
Age: 30-39		-0.214*** (0.026)
Age: 40-49		-0.359 (0.194)
Age: 50-66		0.027 (0.017)
£16,000-29,999		0.069*** (0.020)
£30,000-49,999		0.115*** (0.018)
£50,000-69,999		0.060* (0.028)
£70,000-99,999		0.056* (0.026)
£100,000-149,999		0.085** (0.028)
More than £150,000		0.094** (0.030)
PNTS		0.058 (0.041)
Observations	3,994	3,993
R^2	0.005	0.030
Adjusted R^2	0.004	0.026
Residual Std. Error	0.409 (df = 3989)	0.404 (df = 3975)
F Statistic	5.118*** (df = 4; 3989)	7.175*** (df = 17; 3975)
Note:		*p<0.05; **p<0.01; ***p<0.001
		Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.
		Constants are not displayed as there are no AMEs associated with them.

Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

Table 7. Primary Outcome 2 Results, Experiment 3

	Effect of treatment on Composite Score of Attitude Toward MoneyHelper	
	Primary Outcome 2	
	(1)	(2)
Headstart Framing	0.018 (0.013)	0.018 (0.013)
Present Bias	-0.021 (0.014)	-0.019 (0.014)
Social Norms	0.001 (0.013)	0.001 (0.013)
Specific Questions	0.010 (0.014)	0.010 (0.013)
Gender: Male		-0.116^{***} (0.015)
Age: 30-39		-0.182^{***} (0.016)
Age: 40-49		-0.061 (0.106)
Age: 50-66		0.018 (0.010)
£16,000-29,999		0.030^{*} (0.013)
£30,000-49,999		0.070^{***} (0.014)
£50,000-69,999		0.021 (0.019)
£70,000-99,999		0.043^{*} (0.017)
£100,000-149,999		0.059^{**} (0.018)
More than £150,000		0.073^{***} (0.020)
PNTS		0.077^{**} (0.027)
Observations	3,994	3,993

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Coefficients have been transformed into into average marginal effects (AMEs) for ease of interpretation.

Constants are not displayed as there are no AMEs associated with them.

Model 1 displays the results of just the independent variables impact on the outcome.

Model 2 displays the results of the model with covariates to increase statistical power. The purpose of covariate inclusion is not to interpret their coefficients.

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