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Research Note

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Digital engagement practices: a trading apps experiment

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Equality and diversity considerations

We have considered the equality and diversity issues that may arise from the research in this Research Note. Overall, we do not consider that the research in this Research Note adversely impacts any of the groups with protected characteristics i.e. age, disability, sex, marriage or civil partnership, pregnancy and maternity, race, religion and belief, sexual orientation and gender reassignment.

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Summary

In light of the Financial Conduct Authority's (FCA) Consumer Duty (2022a), and concerns about problem behaviours linked to trading app design (FCA, 2022c), we have conducted an online experiment to investigate the effect of digital engagement practices (DEPs) – including gamification – on trading behaviour. Of particular interest was the effect of DEPs on trading frequency and investment risk, both of which may lead to consumer harm (Barber & Odean, 2000; Hayes et al., 2022). We tested four DEPs, that we observed being used on trading platforms, the use of which has grown substantially in recent years (FCA, 2021b; Hayes et al., 2022; FCA, 2024):

1. "flashing prices" - real-time price changes being indicated with red and green flickers and directional arrows;
2. "push notifications" - frequent pop-up messages about price movements;
3. "trader leaderboard" – a table of traders with the highest returns which participants could attempt to climb;
4. "points & prize draw" – a lottery to which participants received an increased chance of winning if they traded more

In our experiment, these features attracted consumer attention, while conveying no additional information which could improve trading. Our key finding is that DEPs can lead to changes in both trading frequency and investment risk. In particular:

- Push notifications and points & prize draw increased the number of trades made, by 11% and 12% respectively. Flashing prices and trader leaderboard, however, did not statistically significantly increase the number of trades made.
- None of the features led to a statistically riskier investment portfolio at the *end of trading*. Although, push notifications and points & prize draw increased the *proportion of trades* that were in risky investments by 8% and 6% respectively.

Subgroup analysis on our main findings reveals some evidence that DEPs have a larger effect on some subgroups. In particular:

- Those with low financial literacy increased their trading by more than those with high financial literacy in the presence of flashing prices and trader leaderboard.
- Women increased their trading frequency by more than men when push notifications and points & prize draw were introduced.
- Younger participants (18-34) increased their end-of-trading portfolio riskiness by more than older participants (35+) across all DEPs (except flashing prices).

Alongside our earlier work highlighting the association between DEPs and consumers potentially investing beyond their risk appetite (Hayes et al., 2022), this research suggests that firms and regulators should continue to closely scrutinise the effect of trading app design features on consumer investment decisions.

1 Introduction and policy context

Trading apps, platforms that allow users to buy and sell investment products predominantly via applications on their phones, have dramatically transformed the retail investment arena. They have granted consumers much wider access to a variety of products, from fractional shares to riskier assets like cryptoassets and 'contract for differences' (CFDs). They have also packaged this functionality in an interactive interface that, alongside more widespread advertising, has appealed to a wider customer base. In the first four months of 2021 alone, four trading app firms reported 1.15 million new accounts in the UK - nearly double that of all other retail investment platforms combined (Financial Conduct Authority, 2021b). In the three years since, these same four firms have opened a further 2.47 million new accounts in the UK (Financial Conduct Authority, 2024). Many of these new users are younger and possess less investing experience than the average investor (Financial Conduct Authority, 2021a).

While these platforms have increased market participation, the Financial Conduct Authority (FCA, 2022c) and other global regulators (Massachusetts Securities Division, 2020; SEC, 2021; IOSCO, 2022; OSC, 2022; ESMA, 2023; Broihanne, 2023) have raised concerns regarding the design features used by some trading apps and the impact they may have on investor behaviour. Hayes et al. (2022) cited some such features of concern: positive reinforcement (e.g. falling confetti); frequent push notifications; trader leaderboards; and defaults on leverage or investment amounts. Many such features are now referred to under the collective term, digital engagement practices (DEPs) – "design elements or features designed to engage retail investors on digital platforms" (SEC, 2021). This is a definition which subsumes the concept of gamification – "the use of game design elements in non-game contexts" (Deterding et al., 2011).

The concerns are that these DEPs, if successful in increasing user engagement on trading apps, might encourage increased trading frequency and risk taking in a manner inconsistent with the investment objectives of users. The concern about trading frequency is based on research that has demonstrated that trading more - and so incurring more fees and being more likely to succumb to behavioural biases (like selling winning investments whilst holding losing investments) – leads to poorer financial returns (Shefrin & Statman 1985; Barber & Odean, 2000; Barber & Odean, 2013; Gargano & Rossi, 2018). The concern about risk is linked to the fact that many investors do not fully account for the downsides of investing, with almost half of new non-advised investors being unaware that 'losing some money' was a risk of investing (BritainThinks, 2021). The findings from our November 2022 survey added to this literature, showing that in a sample of 3,000 trading app users across five distinct firms, those users of trading apps with more DEPs (what we called 'features of concern') were more likely to: trade more frequently; invest in products potentially beyond their risk appetite (Gneezy & Potters, 1997); and exhibit 'at-risk of problem gambling' behaviours.

However, such a study design cannot conclusively establish that the DEPs tested were the direct cause of these adverse outcomes. The experiment presented in this research note was therefore designed to assess whether there is any direct causal effect of selected design features (flashing prices, push notifications, trader leaderboard and points & prize draw) on investor behaviour, in particular trading frequency and investment risk.

Since trading more or increasing risk-taking has the potential to lead to poor consumer outcomes, especially if consumers are unaware of or are unintentionally changing their investment behaviour as a result of DEPs, this may be of relevance to firms in light of their obligations under the FCA's (2022a) Consumer Duty. The Consumer Duty - which came into force in the UK on 31 July 2023 for on-sale products and services - consists of a set of outcomes-focused rules which compel firms to act to deliver good outcomes for retail customers. It requires firms to act in good faith, avoid causing foreseeable harm and enable and support retail customers to pursue their financial objectives. Of particular relevance to this work is the expectation under the Duty that firms avoid "designing features which exploit the behavioural biases of consumers" (Financial Conduct Authority, 2022b).

2 Behavioural context and treatment design

Digital engagement practices, gamification and deceptive design

Digital engagement practices (DEPs), a term coined by the U.S. Securities and Exchange Commission, are “the tools including behavioural techniques, differential marketing, gamification, design elements or design features that intentionally or unintentionally engage retail investors on digital platforms” (SEC, 2021). Examples of DEPs include frequent push notification with market news (Hayes et al., 2022), other notifications via email and text, interface design drawing attention to specific information and social networking tools enabling users to interact (SEC, 2021).

Many DEPs involve some measure of gamification, generally defined as the “use of game design elements in non-game contexts” (Deterding et al., 2011). Gamification often includes offering progressive rewards such as accumulating badges or points, enabling users to benchmark their performance against others, and increasing the odds of winning prizes based on user engagement. It can also include elements like celebratory messages and visual confetti, although the novelty of such immediate affirmations can diminish over time (Rodrigues, 2022). Outside the investment world, other popular apps such as Duolingo (Huynh, et al., 2018) and Strava (Bitrián, et al., 2020) use gamification features to foster competition and achievement, designed to keep users coming back to the app. We found consistent evidence that incentives for repeated visits enhance app usage and engagement (Hamari, 2017); (Nacke & Deterding, 2017); (Banuri, et al., 2017) (Andrade, et al., 2016) albeit a majority of research is from other non-financial sectors.

It’s important to note that there may be other types of design features that may not neatly be captured as DEPs but are nonetheless concerning. For example, deceptive design (also referred to as dark patterns), which has been the subject of recent attention from other UK regulators (CMA 2022, ICO & CMA, 2023). Whilst deceptive design has been defined in various ways (Gray, et al., 2018; Mathur, Mayer & Kshirsagar, 2021), we take it to mean user interface elements which could lead consumers into taking actions which may be against their best interests. An example of deceptive design is when the suggested investment amount or leverage offered on an app is defaulted to an inappropriately high amount (Hayes et al., 2022). Another is where the layout of an app makes it hard for an investor to find information, where this could include the need to search, scroll or click around excessively to find out about costs (ESMA, 2023).

Deceptive design such as this latter example, is closely related to the concept of sludge (Thaler, 2018; Sunstein, 2019; Sunstein, 2022). This is friction that creates "unreasonable barriers" for customers, which firms must avoid creating to meet expectations under the FCA's Consumer Duty (Financial Conduct Authority, 2022b). Other such examples of sludge could be the disproportionate burden in unsubscribing for a service when compared to subscribing (Mills et al., 2023). In practice, DEPs including gamification as well as deceptive design and sludge can overlap. However, the key question of interest in this research is what effect these design features have on the consumers of a given product or service.

Treatment design

The trading app features tested in this experiment were selected based on our judgement of their prevalence across the trading apps we reviewed (Hayes et al., 2022); the extent of their potential impact on consumers; the feasibility of testing them in an online experiment; and the merit our results would have given existing findings in the literature. Table 1 gives an overview of the treatments we tested.

Table 1. Treatment Conditions

Treatment group	Description
Control	Trading functionality native to the app without the addition of any design features.
Digital engagement practices	
Flashing prices	On the trading screen, prices flickered red (for a fall in price) and green (for an increase in price). These flashes were accompanied by directional arrows, down (for a fall in price) and up (for an increase in price).
Push notifications	Frequent pop-up notifications informed participants about market moves e.g *Is it time to buy or sell? Company F had recent gains!* These were displayed both on the trading screen and the transcription task – designed to capture the fact that notifications can appear when an investor is not actively using an app. A new notification appeared every 15 seconds and remained on screen for 10 seconds. The notifications only appeared for medium-risk and high-risk investments (company shares) and not low-risk investments (funds).
Gamification features (also considered digital engagement practices)	
Trader leaderboard	Participants are shown a list of top traders and their returns. For ease of design, the traders and returns that populated the table were taken from an earlier pilot experiment. However, participants were shown live how they compared to those earlier participants and could compete to move up the list by trying to maximise their returns. The leaderboard was shown on the trading screen only.

Points & prize draw	After finishing their initial fund allocation, participants received a congratulatory pop-up saying they had won 1000 points. They then had a 70% chance of receiving 1000 points for each subsequent buy trade. Participants were informed that the more points they won, the higher the chance they had of winning the £10 prize. A running total of their points earned was at the top of the screen. The prize draw was worth an expected 0.1p to each participant, given the total number of participants in the experiment (~10,000).

Based on the behavioural science literature, set out below, we expected that these digital engagement practices including gamification were likely to increase trading frequency and could also increase risk-taking.

Flashing prices

As far as we are aware, there is no literature that explores the effect of flashing prices in the trading app context. In line with existing literature (Wolfe & Horowitz, 2017; Mullett, Smart & Stewart, 2017), however, our hypothesis was that the visual stimulation of the treatment via the frequent colour changes would capture consumer attention and lead to more time on the app and more trades as a result.

Stock leaderboards, which show the best performing or most popular stocks, have some similarity to flashing prices insofar as recent performance is made more salient to investors which may prompt reallocation of funds. The Ontario Securities Commission (OSC, 2022) investigated the effect of stock leaderboards (amongst other DEPs) on trading behaviour in an online experiment. In their setting, study participants traded $10,000 in experimental money over seven simulated weeks of share price movements, with an option to trade between each week. They found that showing participants a list of top-traded stocks did not increase trading frequency but did increase the likelihood of participants to trade popular stocks by 14%. Similarly, displaying leaderboards for stocks that have seen the largest price changes in the last 24 hours have been shown to drive consumers to pay attention to and trade on the basis of this information, making poorer returns as a result (Barber et al., 2022).

Push notifications

Recent research has demonstrated that notifications appear to increase trading frequency. For example, Moss (2022) found that push notifications concerning price movements of +/-5% increase retail consumer trading on Robinhood by 25% in the immediate time-period following their receipt. Further, Arnold, Pelster & Subrahmanyam (2022), analysing the records of a large broker who send notifications to retail investors, found that those notifications – which concern substantial intra-day price changes, sustained multi-day price changes and earnings report dates - lead people to trade using higher leverage. The authors find the effect is largest for younger, male and less experienced investors.

In an online experiment, Chapkovski, Khapko & Zoican (2021) explored the effect of notifications on trading behaviour. In the experiment, participants were given the opportunity to buy and sell a virtual risky asset over four rounds of trading. Each round lasted 5 minutes and every 5 seconds the price of the asset changed. If the price increased or decreased three times in a row, then participants received a price notification. With unpredictable prices - where past price changes do not affect future price changes, rendering the notifications uninformative - the authors found that some participants correctly do not respond to these notifications. However, others incorrectly think the prices will return to their mean and trade 'irrationally'; selling (buying) following notifications about successive prices increases (decreases).

Trader leaderboards

To our knowledge, the effect of trader leaderboards on trading behaviour has not been tested. However, wider evidence suggests that leaderboards, which by their nature increase social comparison and may affect motivation, can influence behaviour in other domains such as education (Subhash and Cudney, 2018) and health and well-being (Johnson et al., 2016).

Some DEPs comparable to leaderboards have been considered in a trading environment. For example, Broihanne (2023) investigated the effects of a copy trading feature. Their laboratory experiment, commissioned by the Autorité des marchés financiers (AMF), followed Langer and Weber's (2008) allocation of an endowment between a risky asset and a safe asset in 16 successive periods. The authors found that a copy trading feature which allowed participants to copy the allocation of the top performing participant in the previous 4 periods led to more funds being allocated to the risky asset.

Points & prize draw

The aforementioned OSC (2022) study found that participants who received points of negligible economic value for trading stocks increased their trading activity by 39%. The points in that study were not, however linked to a prize draw but rather were directly convertible to at most a very small payoff (≤$0.08).

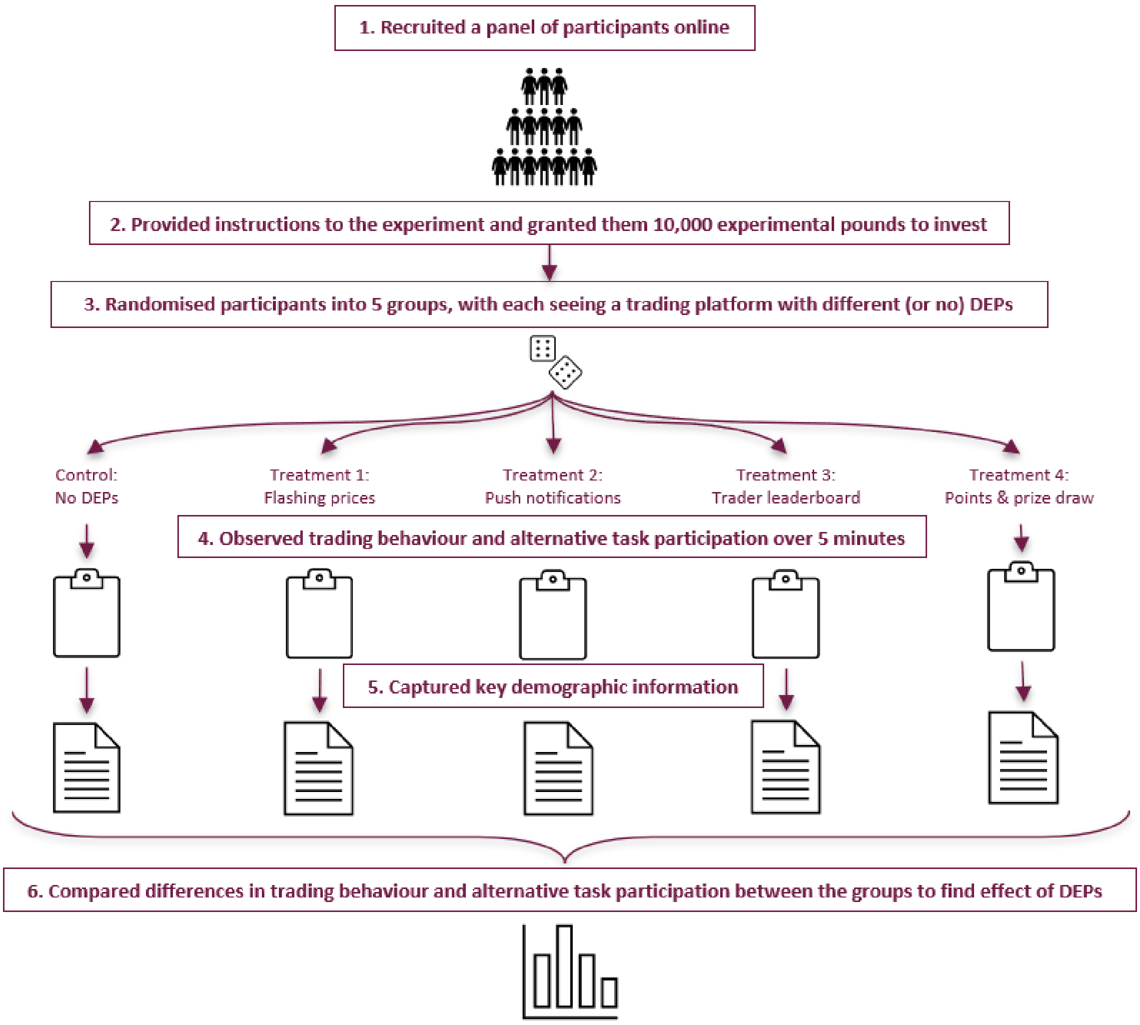
Whilst not directly rewarding points for trading other studies have considered other awards or immediate congratulatory feedback for making trades. Broihanne (2023) paper found that symbolic achievement badges - of no economic value - could increase allocation of funds to the risky (safe) asset if awarded for achieving a risky (safe) portfolio. However, the introduction of 'hedonic stimuli' (like a burst of confetti or encouragement messages after trades are made) did not influence risk-taking in their setting. On the other hand, Chapkovski, Khapko & Zoican (2021), did find that hedonic gamification (celebratory messages and achievement badges) was associated with an increase of trading volume by 5.2%. The increase in trading activity was even larger (12.5%) for those who said they preferred platforms with more hedonic design, who also generally had lower financial literacy.

3 Methodology and sample

Experimental design

We recruited participants through Prolific.co, an online panel provider, which enabled access to a large pool of UK-based consumers. Those participants were then engaged in an online simulated investment scenario via a hypothetical trading app built in oTree (Chen, Schonger & Wickens, 2016), a platform which allows interactive experiments to be implemented. The basic experiment flow is outlined below.

Figure 1: Experiment flow



Prior to the beginning of the experiment, we wrote a *trial protocol* specifying the overall design of the experiment, our treatments, outcomes measures and our empirical (analytical) strategy. We also completed an ethics review to consider and mitigate any risks to the rights, dignity, and welfare of participants. Finally, we conducted a short pilot to ensure there were no errors in the implementation of the experiment that might cause rates of attrition (participants not completing the experiment) to be unexpectedly high.

At the start of the experiment, participants were allocated a real money endowment, denominated in 10,000 experimental pounds (£0.50 equivalent). We used real money and informed participants that they will keep any trading gains to align their incentives to trade optimally (Nieboer, 2020). Participants were then invited to allocate those funds across the 9 generically named financial instruments (6 companies' shares and 3 funds) presented on the app (Figure 2). Each of the financial instruments had an information icon button which, when clicked, would display past performance and a risk score. There was an equal number of low (risk score = 1), medium (risk score = 3.5), and high (risk score = 10) risk investments available (Figure 3). The order in which these investment products were presented in the trading app was randomised for each participant.

Figure 2. Trading app platform – initial screen

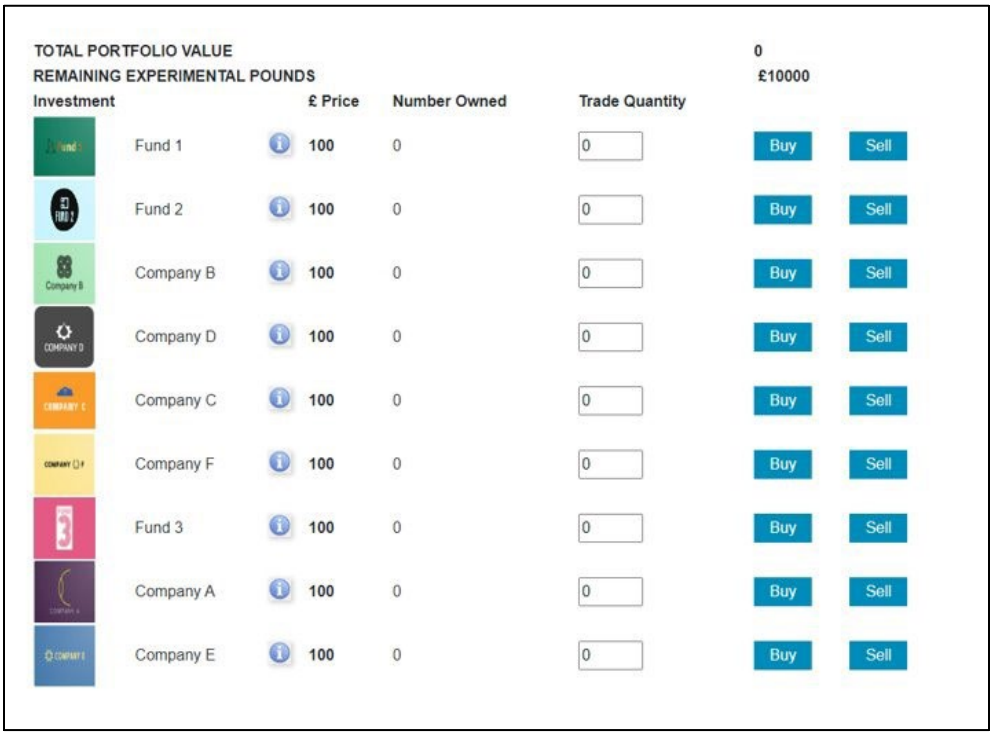


Figure 3. Example of key information (available when clicking on the information icon)

After participants made their initial investment decisions, the prices of the instruments were then allowed to vary in the app - in relation to their risk score but otherwise unpredictably around an average growth rate of 4% per trading period (see Annex 1: for more detail). The experiment lasted for 5-minutes, with each minute corresponding to one trading period, such that there were 5 trading periods and an overall growth rate of 22% across the experiment. During that time, participants were able to toggle between the trading app – where they could continue trading – and an alternative money-earning task. In either case, participants' investments would continue to fluctuate in value.

The alternative task was a simple real-effort task (Charness, Gneezy & Henderson, 2018; Benndorf, et al., 2019) which compensated participants (200 experimental pounds or £0.01) for each time they correctly transcribed the short combination of letters and numbers they were presented with. We included the alternative task with a view to improve external validity; to make the experiment more comparable to a real-life situation. The introduction of the alternative task creates an opportunity cost of engagement with the app, and it also allows us to test our DEPs – in particular, push notifications – in a setting where they can appear when participants are *not* using the app.

There were no trading fees during initial allocation. However, if participants opted to continue trading on the app after the initial allocation, the value of each subsequent trade was subject to a 2% trading fee. Participants were informed about this fee after the initial allocation stage but prior to further trading on the app. Beyond the initial instructions, the fees on each trade and cumulative fees incurred were not highlighted to participants after each trade. This follows the practice we observed on some trading apps where any costs associated with trading are automatically implemented but are often not prominent. We are aware that for not all firms, and indeed for not all products, are fees charged in direct proportion to trading volume. However, we wanted to test if DEPs changed trading behaviour, even in a setting where fees disincentivised trading.

As prices moved unpredictably around a fixed growth rate, and there were trading fees imposed on each trade, the optimal strategy – regardless of treatment – was to refrain from trading after allocating all funds. This strategy has the additional benefit of allowing participants to focus instead on maximising earnings via the transcription task.

As described, the experimental task was identical across participants, except for the introduction of our treatments. Figure 2 and Figure 3 depict the consistent visual features of the trading app utilised in both control and treatment conditions. The corresponding illustrations for all four distinct treatments are exhibited in Figure 4 through Figure 9 below. Further details of the additional features specific to the treatment conditions are outlined in Table 1 above.

Figure 4. Flashing prices on the trading screen

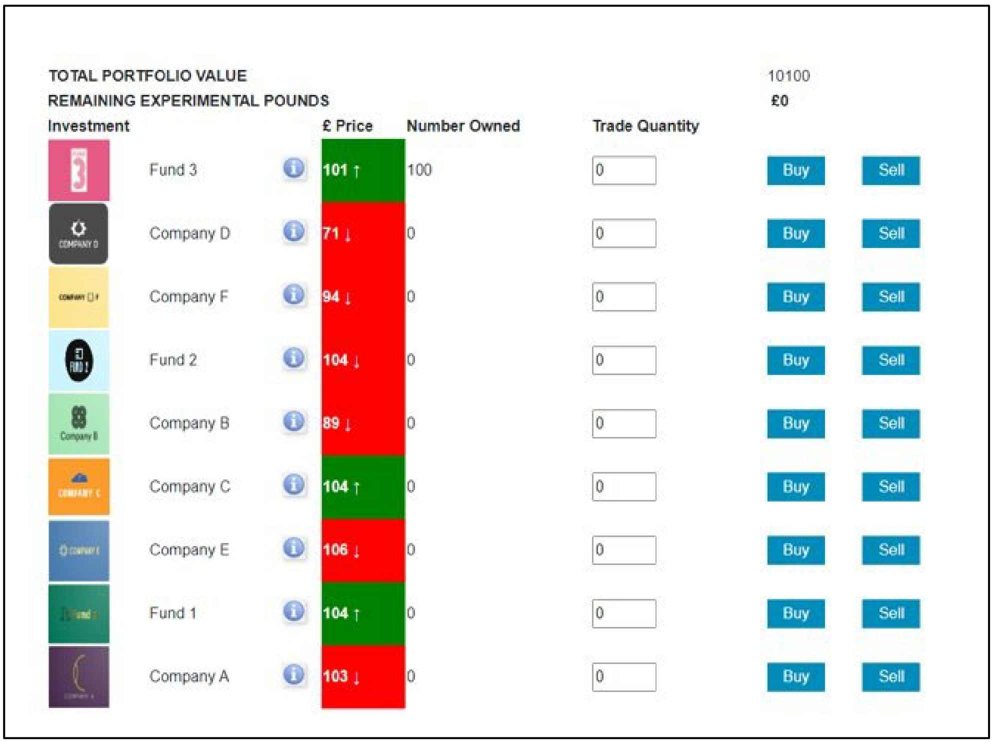


Figure 5. Push notifications on trading screen

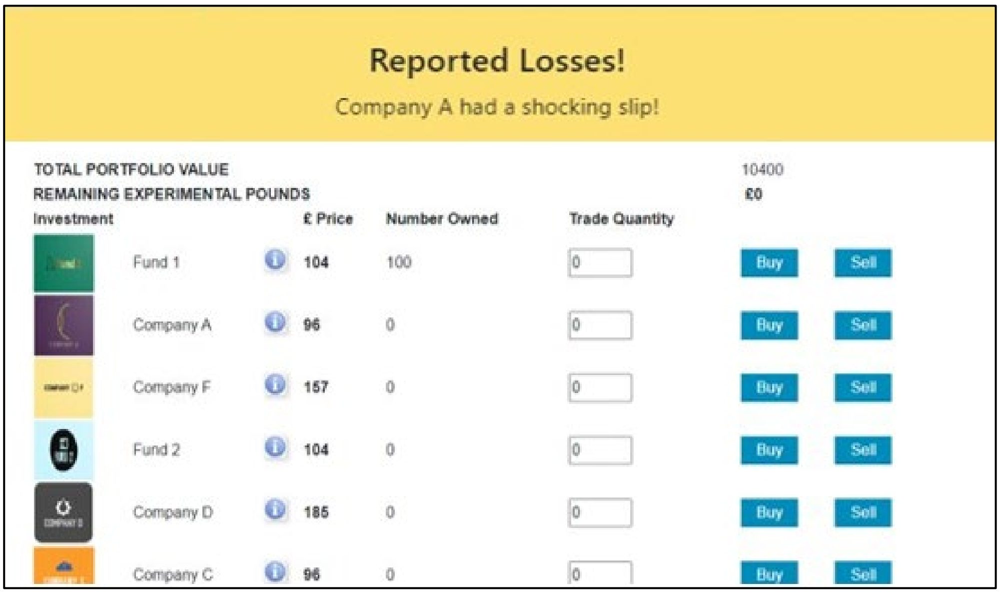


Figure 6. Push notifications on transcription task screen

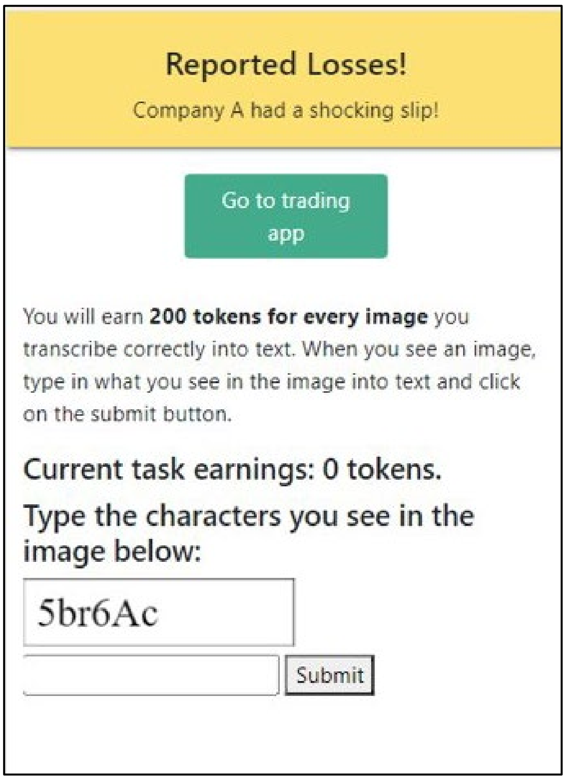


Figure 7. Trader leaderboard on the trading screen

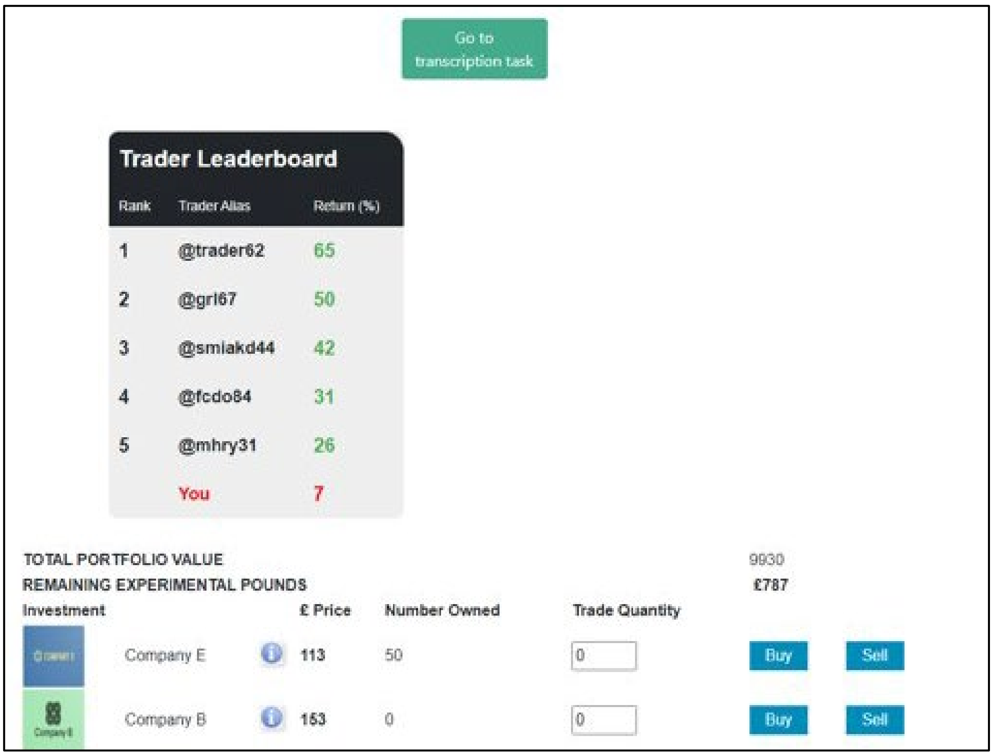


Figure 8. Points & prize draw - pop-up message

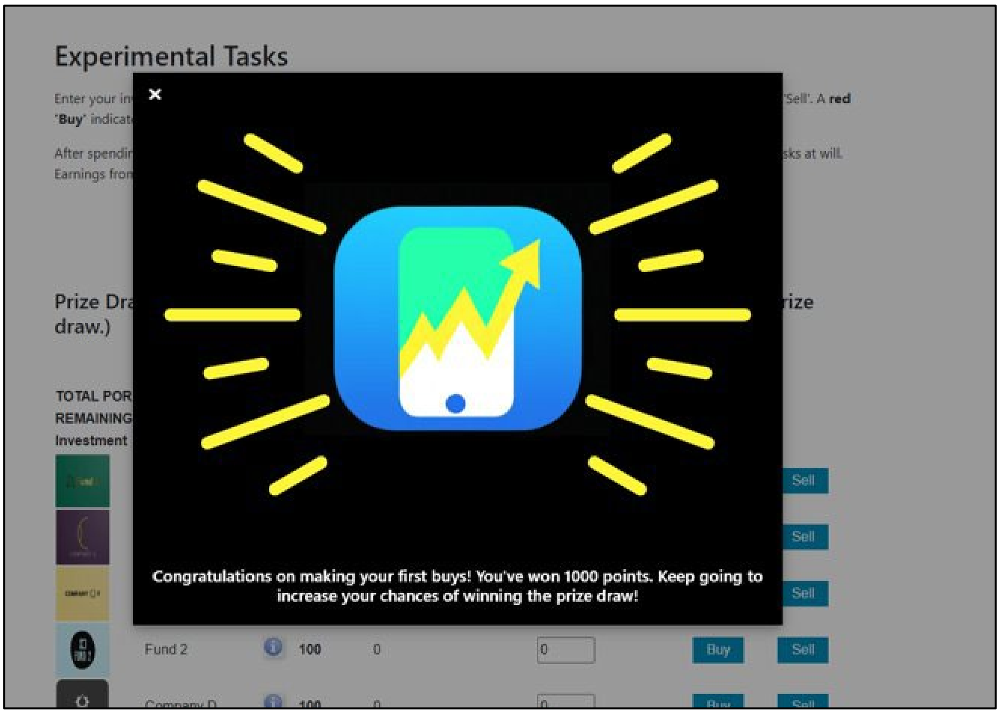
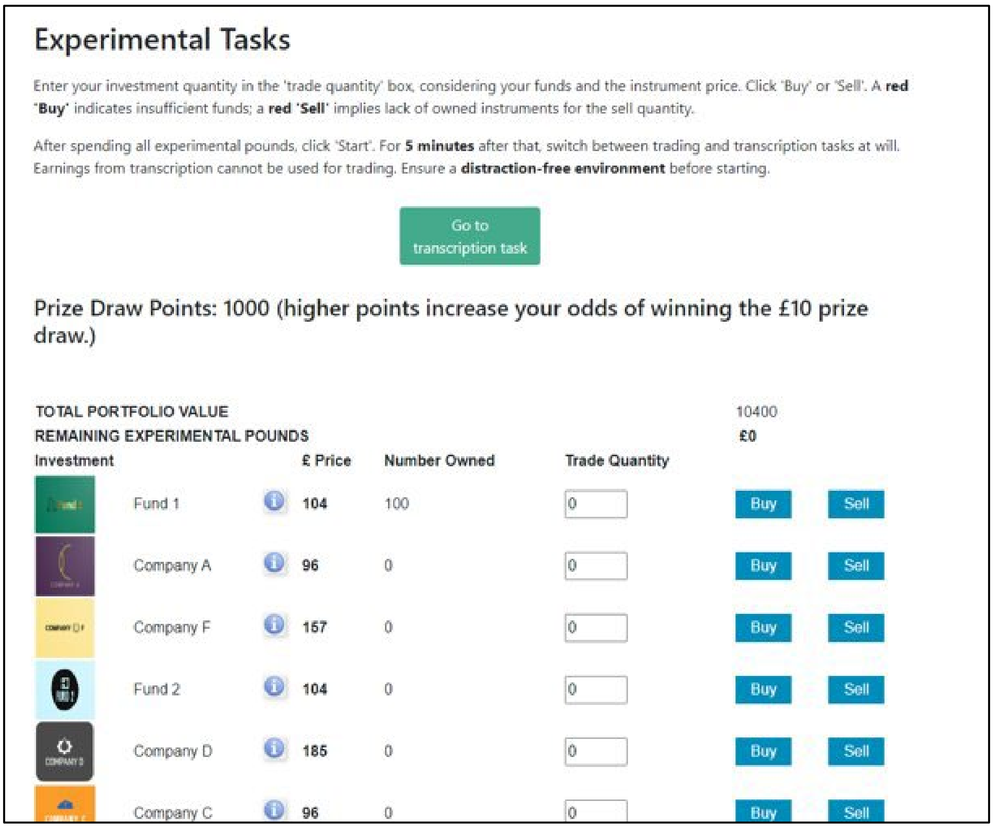


Figure 9. Points & prize draw - points tally



Outcome measures

To measure the impact of trading app design features on consumer behaviour, we specified four groups of outcome measures to look at: trading volume, trading risk, engagement and trading results.

We selected these measures because, as discussed in our introduction, they may be predictive of poor or unexpected financial outcomes. In regard to trading volume, those who trade the most - and so are likely to incur the most fees and exacerbate any trading biases - achieve lower returns than those who trade less frequently (Barber & Odean, 2000; Gargano & Rossi, 2018). In terms of risk, with some investors already underestimating the risk of investing (BritainThinks, 2021) the question is whether DEPs further increase risk-taking, as indicative evidence suggests is the case (Hayes et al., 2022). In terms of engagement, spending longer on the app comes with opportunity costs. However, this could be attenuated by being better able to select investments more aligned with one's risk preferences or select investments that have performed well and could in principle continue to (Gargano & Rossi, 2018). Finally, trading results captures whether financial outcomes have changed by the end of the experiment, which may be moderated by how much investors keep invested.

Table 2 below specifies each individual outcome measure we looked at, a description for that measure and the econometric model we used to analyse changes in that measure. We also classified outcomes as:

1. Primary: the key outcomes monitored in the experiment.
2. Secondary: a form of supporting measure to the primary outcomes (in the cases where these are alternative specifications of the primary outcome measure) or as additional measures designed to add wider contextual insight.
3. Exploratory: were undertaken, following initial analysis of the primary outcome measures, to better understand our treatments effects on trading behaviour. These were not pre-specified before starting the experiment.

Table 2. Outcomes and empirical strategy

Outcome	Description	Analysis type	Model used
I. Trading volume			
1. Trading frequency	The number of trades made during the experiment.	Primary	Negative binomial
2. Shares bought	The number of total shares bought throughout the experiment.	Exploratory	Negative binomial
II. Investment risk			
3. Investment risk - final portfolio	The proportion (0-1) of shares owned that were in the riskiest products (risk score = 10) at the end of trading.	Primary	Beta
4. Investment risk - trades made	The proportion (0-1) of trades made throughout the experiment that were in the riskiest investments (risk score = 10).	Secondary	Beta
5. Investment risk - shares bought	The proportion (0-1) of total shares bought throughout the experiment that were in the riskiest investments (risk score = 10).	Exploratory	Beta
6. Diversification	The extent to which the portfolio at the end of trading is diversified (0-1). Diversification is a risk-mitigation strategy that involves spreading funds across a variety of investments. The diversification score is taken from OSC (2022).	Exploratory	Beta
III. Engagement			
7. Engagement – alternative task	The number of transcriptions completed in the task offered as an alternative to trading.	Secondary	Linear
8. Engagement - key information	The number of times information on stocks (with past performance and risk score) was opened.	Secondary	Negative binomial
IV. Trading results			

9. Amount uninvested	The amount not invested at the end of the experiment, as a percentage of the starting endowment.	Secondary	Linear
10. Trading earnings	Earnings made from trading, as a percentage change in comparison to the starting endowment.	Secondary	Linear

Empirical strategy

We conducted an online randomised controlled trial (online experiment) (Nieboer, 2020). We evaluated each of our treatments independently (as opposed to combining them) to understand their effect in isolation as compared to a control with no DEPs. We utilised a between-subject design - where each participant was allocated to either the control or one treatment. This ensured that each treatment was uniquely administered to a distinct group, a deliberate design strategy to isolate and understand the impact of individual trading app features on trading behaviour. The regression models we used for each outcome are stated above in Table 2.

In each of our analyses, we run the relevant model both with and without covariates for robustness. However, as per our pre-specification, we report the effect of our treatments on the outcomes of interest from the model without covariates. For models where the effect size is not readily interpretable (i.e. negative binomial and beta models), we report the average marginal effect, obtained using the margins package in R (Leeper, 2021). Accompanying the reported effect size, we also provide an estimate of the associated percentage change. To calculate this percentage change, we compare the effect estimated in the relevant model against the average outcome observed for participants in the control condition.

The covariates we collected (at the end of the experiment) and control for are: gender, age, income, education, employment status, financial literacy, financial resilience, whether our participants are trading app users and whether they completed the experiment on a mobile. We used some of these measures, as well as an amended version of the problem gambling severity index (PGSI) score (Ferris & Wynne, 2001) for subgroup analysis, where we include an interaction term between the treatments and the covariates in question. We set out all covariates in more detail in Annex 2:.

In our primary analysis, we correct for multiple hypothesis testing by using Bonferroni corrections (Abdi, 2007). This means we have divided the traditional significance threshold ($\alpha = 0.05$) by the number of comparisons we make in our analysis. We take the number of comparisons to be four for each of our hypotheses, four treatments compared against one control. With this higher threshold for significance ($\alpha = 0.0125$) we help reduce the chance we erroneously find a significant result when making multiple comparisons in our primary analysis. The secondary and exploratory analyses do not include Bonferroni corrections. As a result of this approach, we can place more confidence in the findings from our primary analysis than our secondary and exploratory findings.

Sample description and attrition

In our study, we collected a sample of 9,140 complete responses. We determined our approximate desired sample via power calculations informed by the OSC's (2022) experimental results. Table 6 in Annex 2: describes our sample. We recruited to ensure that around half our sample were trading app users and that there was an equal balance of males and females. Around 60% of the recruited sample were between 25-44 and about 40% conducted the experiment on their mobile phone.

To check whether randomisation of participants across treatments was successful, we tested whether demographic and financial characteristics are balanced across treatments. We found our sample is balanced across all our covariates except for income. The observed imbalance in income does not appear to be systematic.

We also examined attrition in our experiment. Attrition rates were relatively high at 15.1%, with 1,624 participants leaving the experiment before completion. This may reflect the fact that the experiment was relatively complex, which may have deterred people from finishing it. Of all the participants that started the experiment, 6.2% left during the instruction pages, whilst 8.2% left during the 5-minute trading period. However, we found no differential attrition across the treatment groups. In particular, a chi-squared test shows found no significant difference in terms of either the total proportion leaving the experiment (*X-squared = 37.989, df = 40, p-value = 0.5611*) or stage at which participants left the experiment (*X-squared = 6.8936, df = 4, p-value = 0.1416*) across treatments.

4 Results

We summarise the effect of the digital engagement practices (DEPs) on each outcome measure in Table 3, below. An arrow pointing upwards indicates that we found that the DEP increased the associated outcome measure, whilst an arrow pointing downwards shows that the DEP reduced the associated outcome measure. No arrows indicates that we did not find a statistically significant relationship.

Table 3: Summary of results

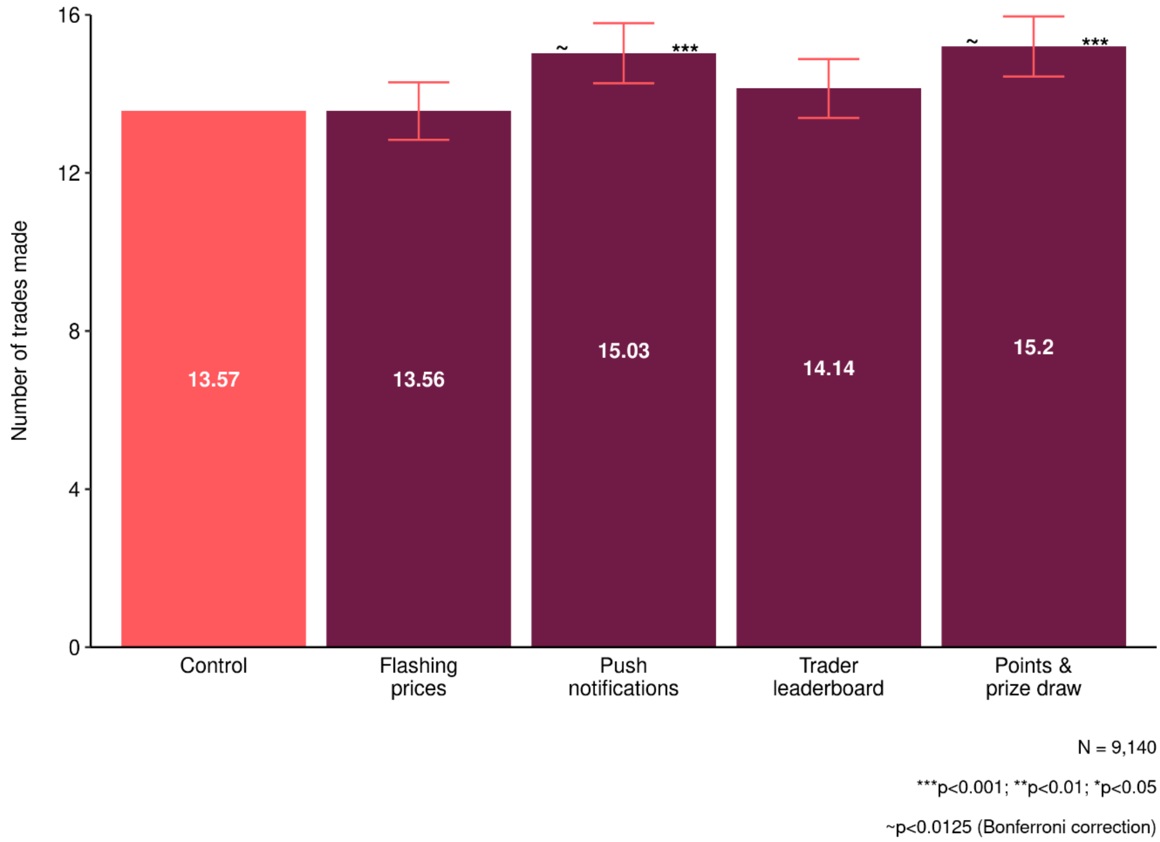
	Flashing prices	Push notifications	Trader leaderboard	Points & prize draw
I. Trading volume				
1. Trading frequency	-	↑	-	↑
2. Shares bought	-	↑	↑	↑
II. Trading risk				
3. Investment risk - final portfolio	-	-	-	-
4. Investment risk - trades made	-	↑	-	↑
5. Investment risk - shares bought	-	↑	↑	-
6. Diversification	-	-	-	-
III. Engagement				
7. Engagement – alternative task	↓	↓	↓	↓
8. Engagement - key information	↓	-	-	-
IV. Trading results				
9. Amount uninvested	-	↑	↓	-
10. Trading earnings	-	-	-	-

Trading volume

The push notifications and points & prize draw treatments significantly increased trading frequency, whereas the flashing prices and trader leaderboard treatments did not.

Participants who received push notifications or who had the opportunity to earn points linked to a prize draw made 1.5 trades (11%), and 1.6 trades (12%) respectively when compared to the control group, where 13.6 trades were made on average (see Figure 10 below and Table 7). These results are robust to the inclusion of covariates. The analysis with covariates reveals that those that are younger, female or who conducted the experiment on a desktop are likely to trade more frequently. No other demographic or financial measures led to statistically significant difference in trades made.

Figure 10. Trading Frequency



Our exploratory analysis evaluated the effect of an alternative measure of trading behaviour, the number of shares bought. This analysis supports our primary findings, showing that those who received push notifications or were offered points & prize-draw bought 11.4 (8%) and 9.8 (7%) more shares respectively. In addition, we also find that the trader leaderboard increased shares bought by 8.6 (6%) (see Table 8).

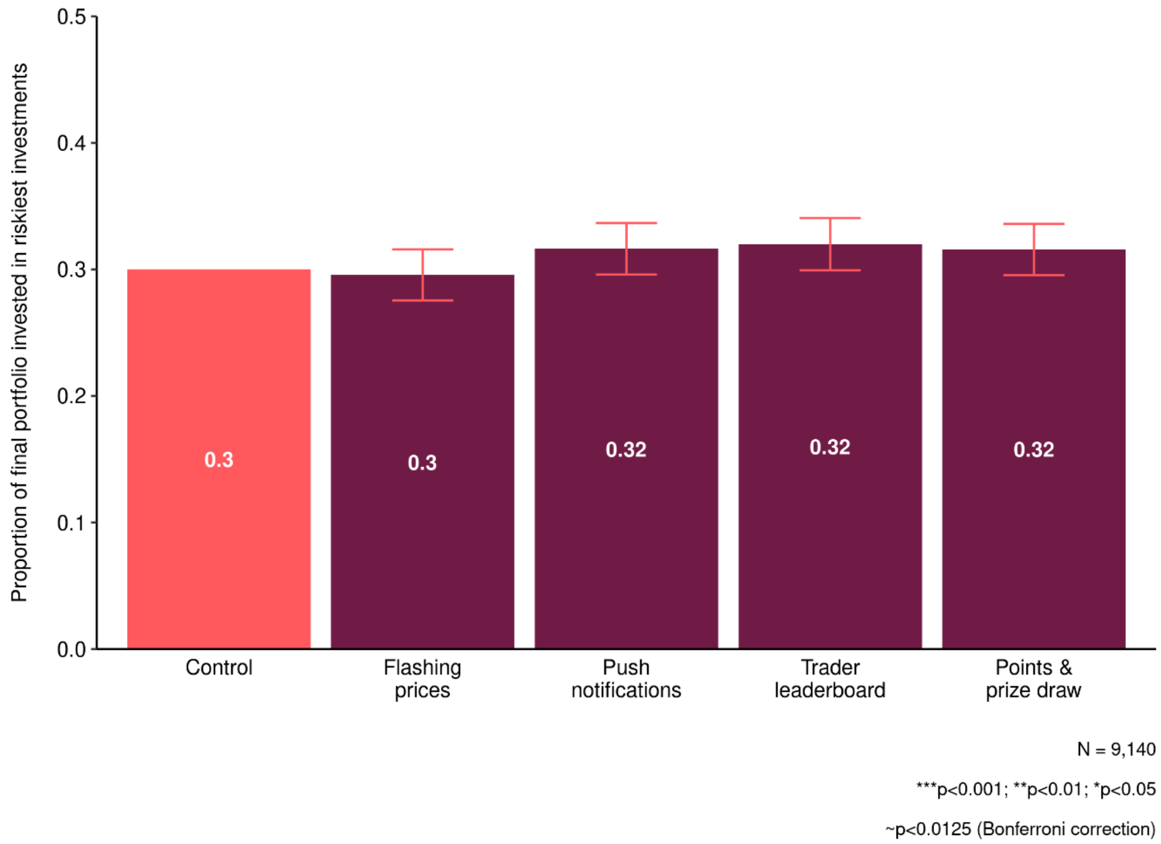
Buying more shares in the experiment is indicative of *trading* more shares overall because participants started the experiment with their full endowment invested and could only buy more shares if they first sold some. This exploratory result is important as it shows that the *higher number of trades* that participants made under DEPs also resulted in *more total shares* being traded, and so likely more trading fees being incurred when DEPs are introduced.

Investment risk

None of the treatments led to a riskier investment portfolio at the end of trading. However, push notifications and points & prize draw treatments significantly increased the number of trades made in the riskiest investments during trading.

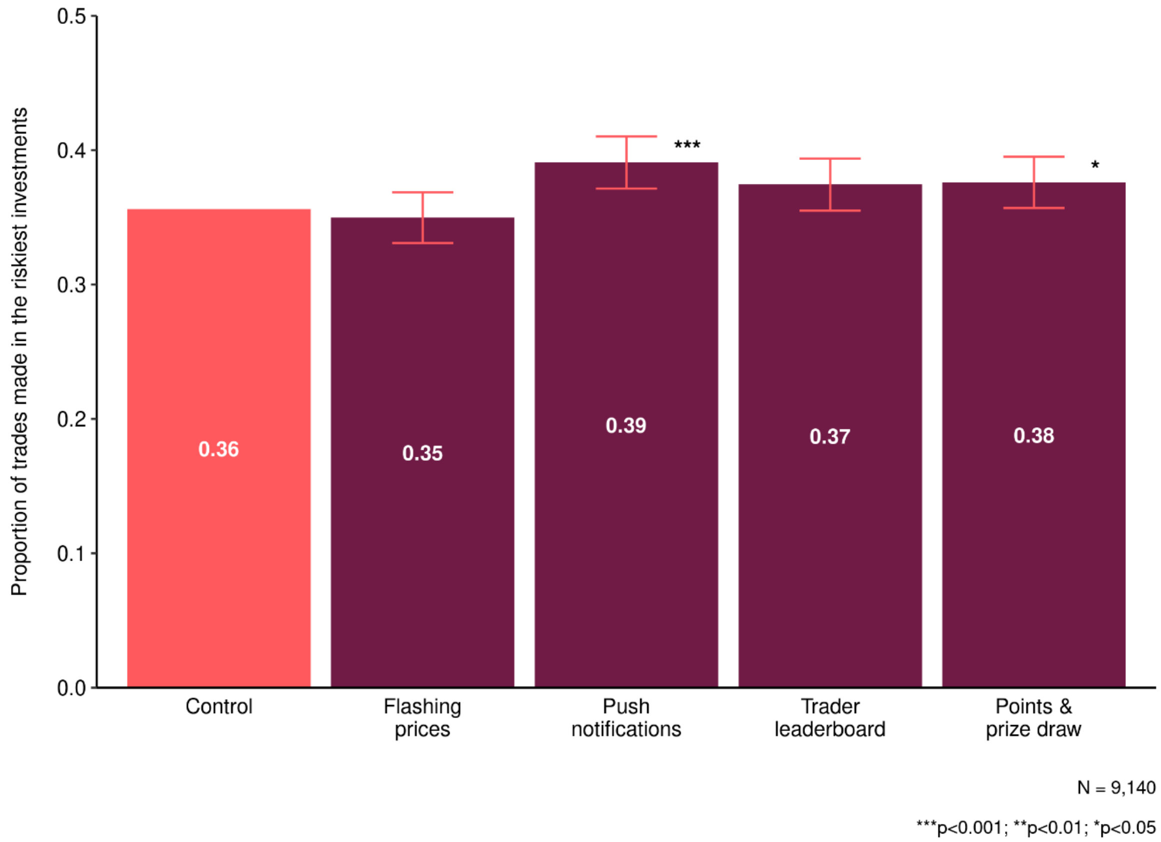
Our primary analysis (Figure 11, and Table 9) shows that for participants in the control, 30% of their portfolio was invested in high-risk investments (risk score = 10) by the end of the experiment. None of our treatments significantly increased the proportion invested in high-risk investments *by the end of trading*. The analysis with covariates shows that males are significantly more likely to have a riskier portfolio by the end of trading.

Figure 11. Investment risk (final portfolio)



Our secondary outcome measure for investment risk looked at the proportion of the trades made *throughout the experiment* that were in high-risk investments. For participants in the control, 36% of trades were made in the riskiest investments on average (Figure 12 below and Table 10). In line with their effect on trading frequency, push notifications and points & prize draw treatments increased this proportion by 3.5 percentage points (pp) (10%) and 2pp (6%), respectively. The analysis with covariates again shows that males are significantly more likely to trade in the riskiest assets. In addition, younger (18-34) participants trade in risky assets more than those who are 35-44 or 55+. The difference in our primary and secondary risk measures is consistent with the hypothesis that there is a higher proportion of *both* buys *and* sells of the risky assets in the presence of some DEPs.

Figure 12. Investment risk (trades made)



As we did with trading frequency, we also undertook an alternative exploratory measure of risk based on the proportion of risky shares *bought* throughout the experiment (Table 11). Under this measure, push notifications again led to a significant increase but this time trader leaderboard rather than points & prize draw led to an increase in risk. As with the other two risk measures, flashing prices did not lead to any significant changes.

Diversification

None of the treatments (flashing prices, push notifications, trader leaderboard, or points & prize draw) led to a less diversified investment portfolio at the end of trading.

We find that none of our treatments are significantly different from the level of diversification in the control, where the diversification score (OSC, 2022) is 0.63 (Table 12). These results are robust to the inclusion of covariates. The analysis with covariates shows that females, younger (18-24) participants and those with a higher financial literacy have a more diversified portfolio at the end of trading. Since one of questions used to determine the financial literacy score (Lusardi & Mitchell, 2011; Lusardi & Mitchell, 2011a) asks whether a diversified portfolio offers a safer return than a single stock, it is intuitive that those with higher financial literacy have a more diversified portfolio.

Engagement

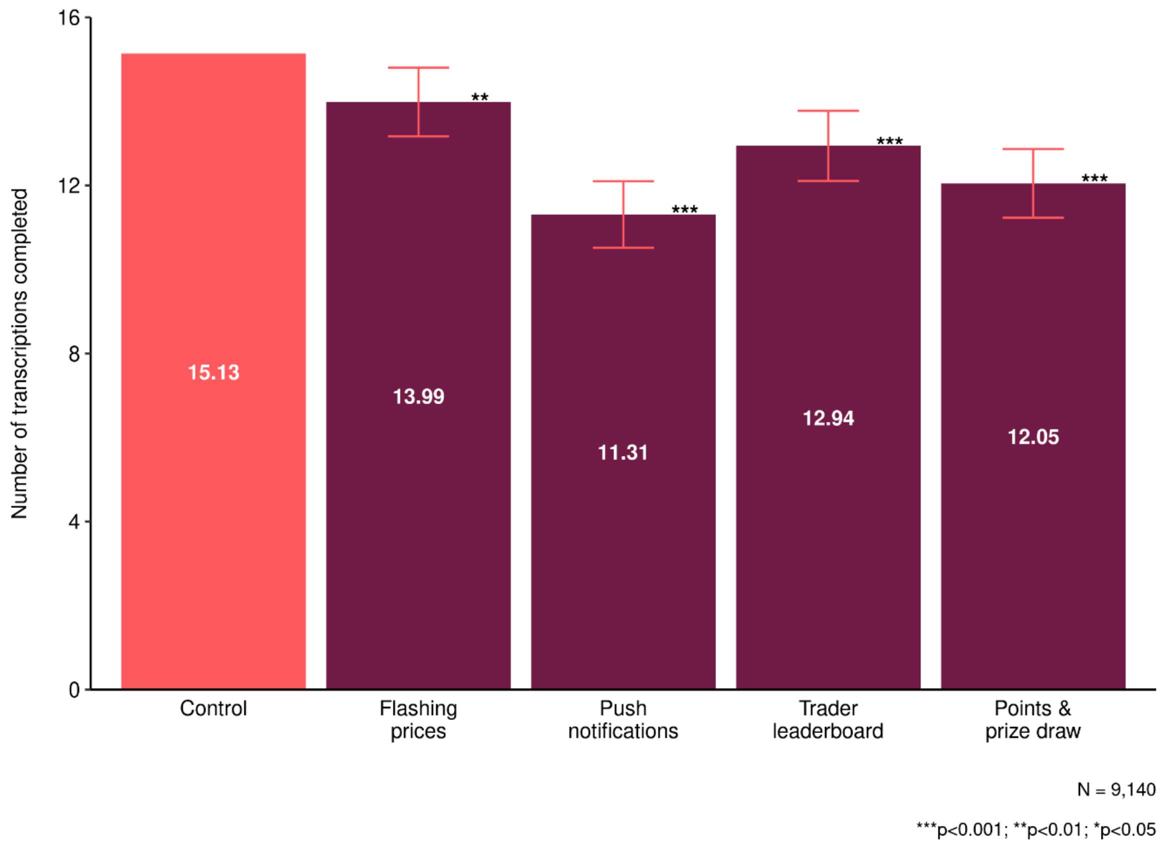
Engagement with alternative task

In all four of our treatments, participants completed fewer alternative transcription tasks – which led to lower earnings compared to the control and highlights that all DEPs captured consumer attention.

In the control group, participants completed an average of 15.1 transcriptions. There was a notable decline in the number of transcriptions completed across all treatments ranging from 1.1 to 3.8, representing an 8% to 25% reduction compared to the Control (see Figure 13 and Table 13). Our results show that those were younger (18-24), female, with high financial resilience, high financial literacy and that participated in the experiment on desktop completed a higher number of transcriptions.

Since transcriptions earnings were directly linked to completions, the associated earnings in this task fell by the same magnitude in each treatment, respectively (e.g an 8% reduction in completions led to an 8% reduction in earnings). In each case, participants likely dedicated more time to the trading app at the expense of the alternative task, demonstrating the efficacy of each of the digital engagement practices in capturing consumer attention. This is true, even in the case of trader leaderboard and flashing prices, which in our experiment did not lead to a significantly higher number of trades.

Figure 13. Engagement with alternative task



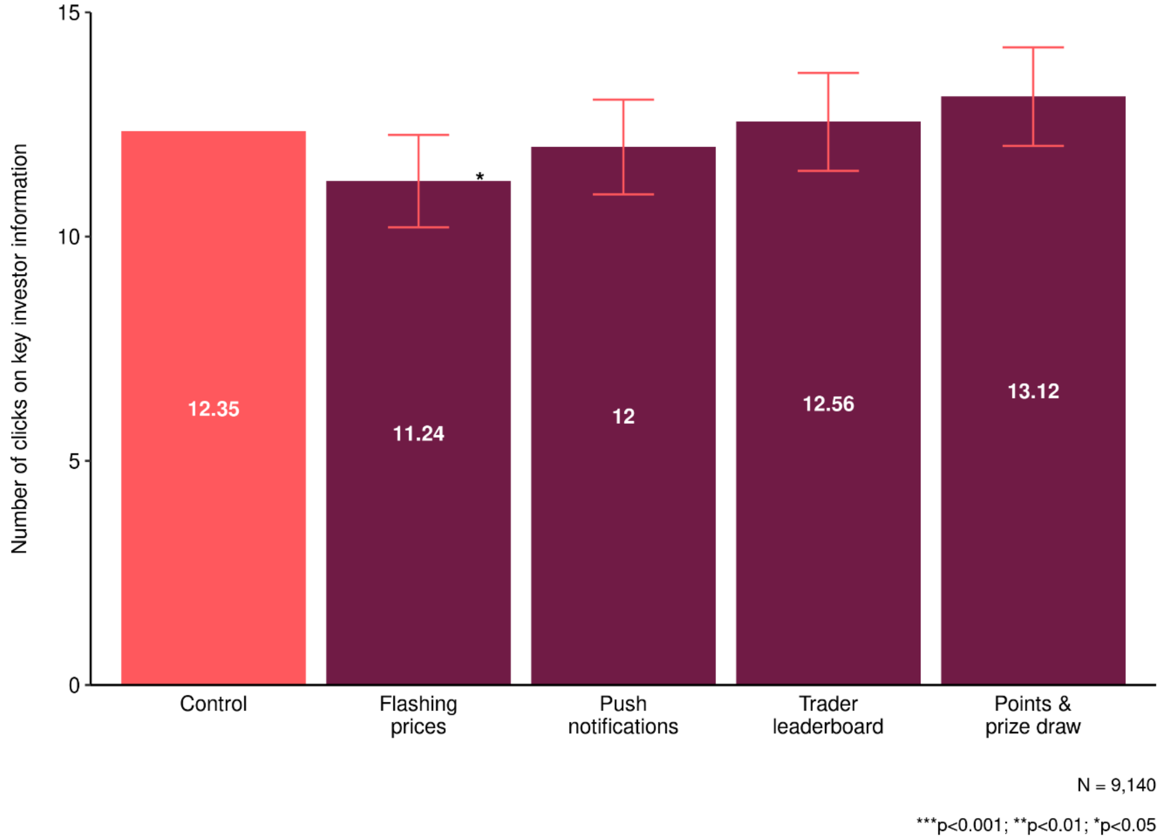
Engagement with key information

The flashing prices treatment significantly reduced engagement with key investor information. The other treatments had no effect.

We find that only the flashing prices treatment led to a significant decrease of 10%, by 1.1 clicks to 11.2, when compared to the control where participants consulted the information button 12.3 times on average (Figure 14 and Table 14). The analysis with covariates shows that those who were younger (18-24), those with a high financial resilience, and those with medium or high financial literacy were significantly more likely to consult the additional information.

When coupled with the results on transcription earnings (above), it is interesting to note that participants appear to be spending longer on the app in the DEP conditions but do not accordingly consult the key information more. This suggest that the additional engagement that the DEPs are encouraging are not funnelling investor attention to key information.

Figure 14. Engagement with key investor information



Trading results

Amount uninvested

Flashing prices and push notifications had no effect on the amount participants had uninvested at the end of trading. Whereas push notifications led participants to leave more uninvested and trader leaderboard led participants to leave less uninvested.

With regard amount uninvested, there was not a clear pattern across the treatments (Table 15). Those in the control had around 26.2% of their initial endowment (10,000 experimental pounds) uninvested at the end of trading. Those who received push notifications left 2.8pp (11%) more uninvested and those who viewed a trader leaderboard left 2.8pp (11%) less uninvested. In other words, those in the trader leaderboard (push notifications) treatment group kept more (less) of the initial endowment invested, when compared to the control. These results are robust to the inclusion of covariates. The analysis with covariates shows that females, those with an income of <£25k and those with higher financial literacy leave less uninvested (had more invested) at the end of trading.

Trading earnings

Higher trading was associated with worse trading returns overall. However, despite the increased trading activity in push notifications and points & prize draw, none of our treatments led to worse trading returns for participants.

As would be expected given the application of the trading fee (2% per trade) on each trade. For each additional trade made, returns were 0.1pp lower (Table 16).

However, we find that trading returns - as a percentage of participants initial endowments - were not significantly different between the treatments and the control, where returns were 22.3% (Table 17). We believe this is fundamentally due to the in-built randomness of the price mechanism for the assets (see Annex 1:) and the relative shortness of our 5-minute experiment. Ultimately, trading earnings is a noisy measure with a standard deviation approaching 28.6pp. This is substantially larger than the cost of trading, which in terms of returns, costs 0.1pp per trade.

Our results on trading earnings are robust to the inclusion of covariates, where we can also note that females and those with high financial resilience receive higher returns. The fact that males make lower returns despite making significantly fewer trades is likely explained by a combination of the fact that they left a higher proportion of their endowment uninvested and that they traded a higher number of total shares.

Sub-group analysis

DEPs have a larger effect on the trading frequency of potentially vulnerable participants - those with lower financial literacy. Women also tend to be more affected. We also find evidence that DEPs have a larger effect on portfolio riskiness at end of trading among younger participants.

From our sub-group analysis on trading frequency, we find that DEPs impact those with lower financial literacy more (Figure 15 and Table 18). Respondents with low financial literacy are significantly more influenced by flashing prices and trader leaderboards than those with medium/ high financial literacy. In fact, this differential effect is such that – as well as points & prize-draw and push notifications - for those with low financial literacy, the presence of trader leaderboards results in a significant increase in trading.

We also find that females increase their trading frequency by more than males when push notifications and points & prize draw are introduced (Figure 16 and

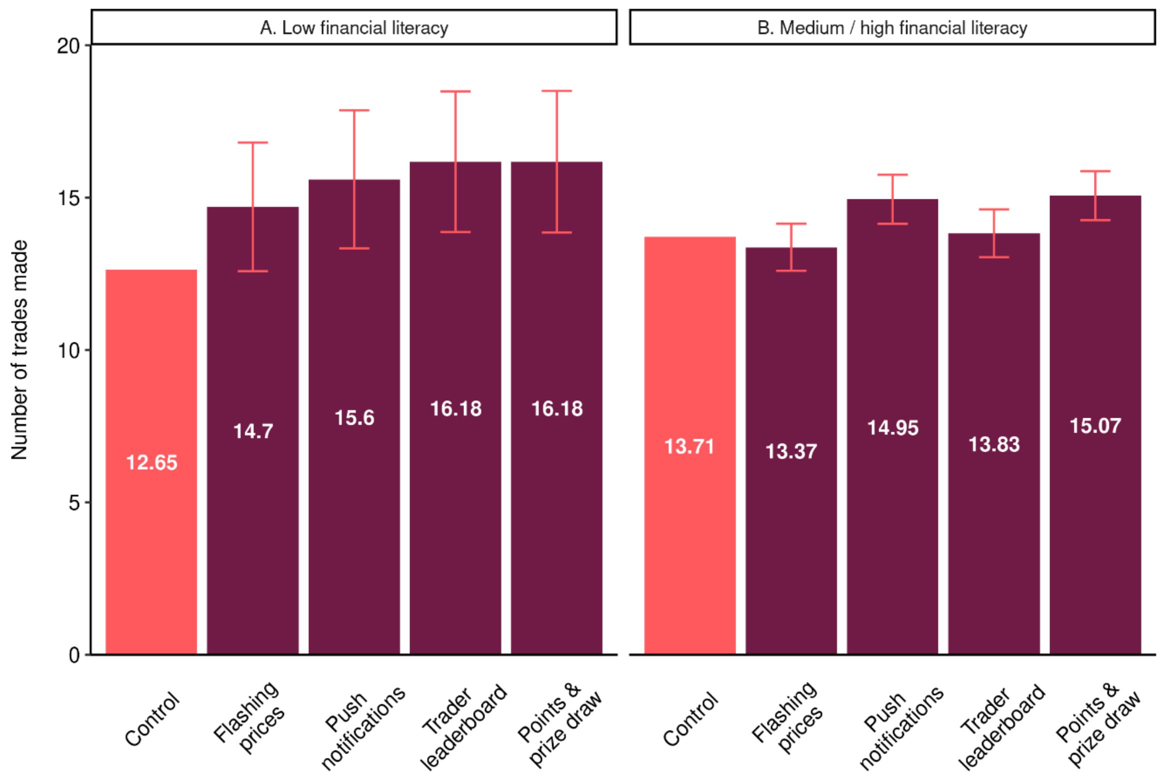
Table 19). In addition, although those aged 18-34 do not trade significantly more in the presence of flashing prices, the effect of flashing prices is significantly larger for those 18-34 than those 35+ (Table 19).

The wider literature finds that women and younger people tend to have lower financial literacy (Lusardi & Mitchell, 2023). Given this, we ran robustness checks controlling for age and gender in our regression with interaction effects between DEPs treatment and financial literacy. We find that the interaction effects remain significant in this specification too (Table 20) adding to our confidence that financial literacy is a key subgroup for concern.

Consistent with the general lack of effect of DEPs overall on portfolio riskiness at the end of trading, we found no evidence of differential effects of DEPs on this measure of risk by gender, income, financial resilience, financial vulnerability, or gambling-like behaviours (Table 21 and Table 22).

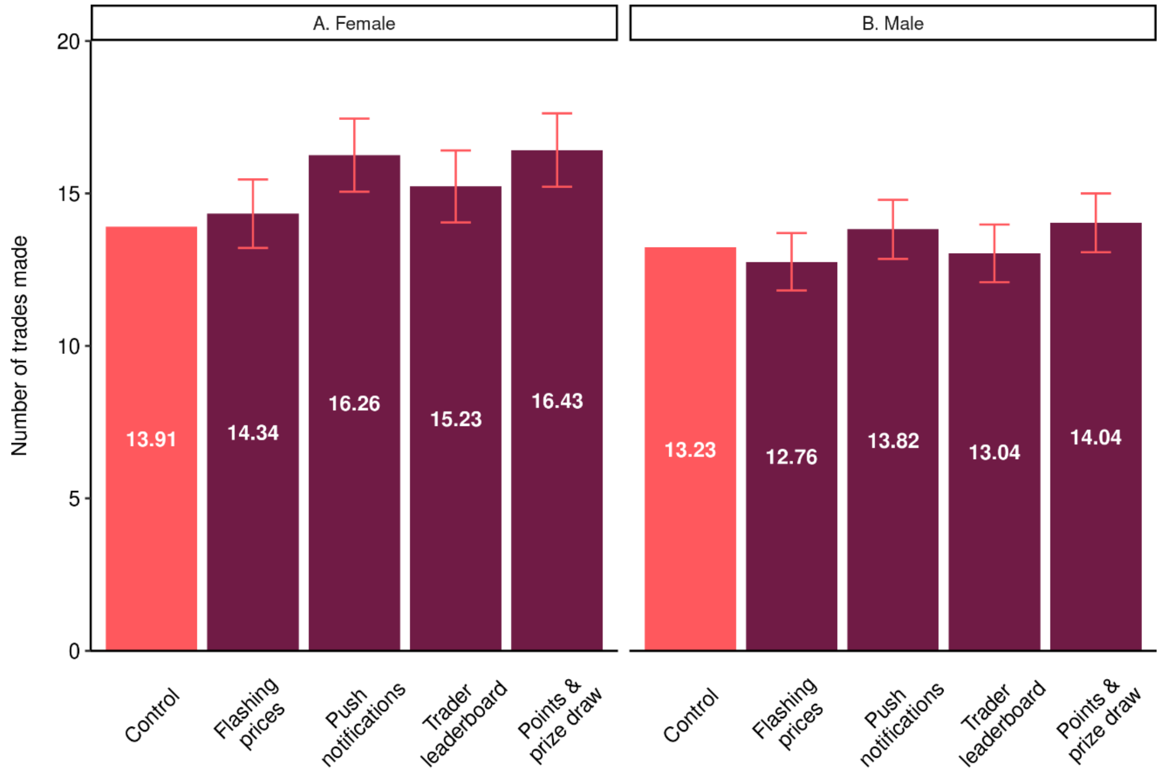
However, we found that portfolio riskiness at end of trading among those aged 18-34 was significantly more influenced by the presence of every DEP, compared to those aged 35+ (Figure 17 and Table 22). In fact, this differential effect is such that, while we observed no overall effect of DEPs on riskiness of portfolio at end of trading among all participants, for those aged 18-34 every DEP (aside from flashing prices) led to a riskier portfolio at the end of trading compared to the control.

Figure 15. Average trading frequency (by financial literacy)



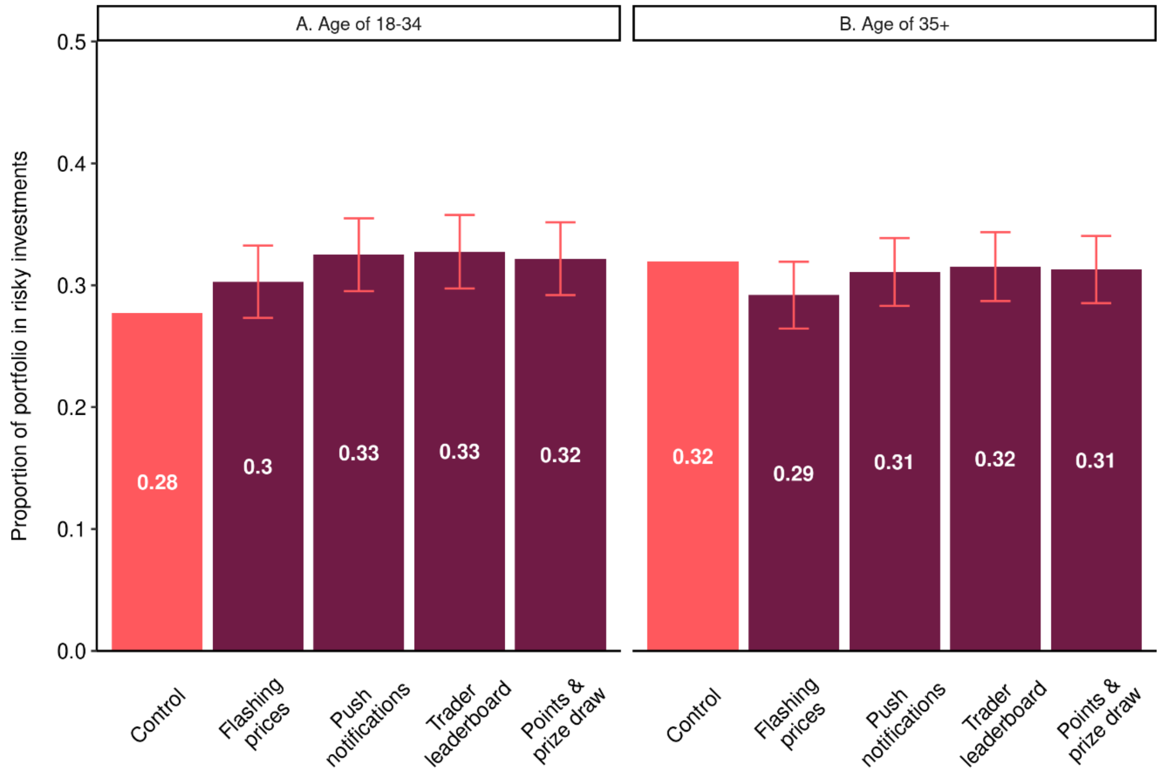
N = 1,186 (Panel A); N = 7,954 (Panel B)

Figure 16. Average trading frequency (by gender)



N = 4,584 (Panel A); N = 4,460 (Panel B)

Figure 17. Riskiness of portfolio (by age)



N = 4,061 (Panel A); N = 5,079 (Panel B)

5 Discussion

The results presented here show that digital engagement practices (DEPs) (SEC, 2021) –including gamification (Deterding et al., 2011) - in trading apps can increase trading volume and the amount of shares traded. Two of the four treatments we tested - "push notifications" (frequent notifications about market moves) and "points & prize draw" (points based on investment behaviour that are linked to a prize draw) - led to increases in trading frequency (of 11% and 12%, respectively) and the quantity of shares traded (of 8% and 7%, respectively). Whilst trader leaderboard (seeing a top list of traders and being able to compete to move up this list) did not increase the number of trades, it did lead to 6% more shares being traded. Since higher trading frequency is associated with lower financial returns (Barber & Odean, 2000), even if not in our experiment, this should give both regulators and firms pause for thought about the effect of DEPs on investment behaviour.

Our findings on trading volume are broadly consistent with the wider literature. For instance, the OSC (2022) demonstrated that a points-based incentive, albeit not linked to a prize-draw, can increase trading frequency. The effect magnitude in their experiment (39%) was, however, substantially larger than the effect in ours (12%), perhaps because there were fees applied in our setting but not theirs. The effect on our significant treatments was in turn slightly larger than the effect observed (5.2%) by Chapkovski, Khapko & Zoican (2023) for the cumulative introduction of hedonic gamification (badges and celebratory messages). Our findings that push notifications lead to increased trading also lend support to recent findings (Moss, 2022).

Whilst none of the DEPs increased the percentage of risky investments held at the end of trading, push notifications and points & prize draw features increased the proportion of trades that were made in high-risk investments, by 8% and 6% respectively. Whilst push notifications – which were only sent for medium and high-risk investments – may have explicitly steered participants towards higher-risk investments, points & prize draw (and other DEPs tested) did not. This raises the possibility that DEPs could encourage higher risk-taking even if the casual mechanism is not immediately obvious. Considering our findings alongside other relevant recent research (Arnold, Pelster & Subrahmanyam, 2022; Broihanne; 2023) our experimental evidence tends to support the view that DEPs - depending on how they are implemented - could lead consumers to take on more risk when investing. This may lead to concerns if DEPs encourage consumers to invest beyond their risk appetite, as suggested by Hayes et al. (2022).

In addition, all four DEPs drew attention from the alternative task towards the trading app. This indicates the ability of DEPs to capture consumer attention, regardless of whether additional trading is conducted. However, this additional engagement was not supported by a commensurate increase in engagement with key information (past performance and risk score) on assets. Neither – in line with OSC (2022) - did DEPs increase diversification at the end of trading. Given the efficacy of DEPs in increasing engagement and trading frequency, this experiment suggests that DEPs could similarly be used to improve trading outcomes, by encouraging consumers to engage with key information on fees and risk information or considering diversifying their portfolio, where appropriate.

Our sub-group analysis found that potentially vulnerable populations may be more susceptible to changing their trading behaviour as a result of DEPs. We find evidence that the effect of DEPs on trading frequency is higher for participants who have low financial literacy. Separately, we also find evidence that women trade more once DEPS are introduced. Our subgroup analysis also highlights that younger groups (aged below 35), are more likely to take on a risky portfolio as a result of DEPs. This is particularly important because many new users of trading apps are younger than the average investor (Financial Conduct Authority, 2021b).

As far as we are aware, this is the first piece of research to test the effect of flashing prices, a trader leaderboard and a points linked prize draw on consumer trading behaviour. Our research has at least four key limitations that may call for further investigation:

1. We investigated four DEPs separately, whereas trading apps often have many DEPs that the consumer is exposed to successively or at once. Future research could assess whether and how the number of trades made, and the risks taken would differ with multiple features implemented at the same time.
2. There are other important questions about the effect of DEPs that were not explored in this experiment. For example, whether DEPs encourage more people to sign up for an app in the first instance, or once signed up to deposit more money for trading or open bigger (more leveraged) positions.
3. Our results do come from an online experiment, which cannot fully capture the real-world experience. In particular it is unable to explore the longer-term effect of DEPs on consumer outcomes or the effect of DEPs with significantly more money at play.
4. There are outstanding questions about the extent of the inverse relationship between trading frequency and trading returns (Barber & Odean, 2000), under the low commission business models prevalent on trading apps today. In addition, there are also ethical questions (Lades & Delaney, 2022) about whether consumers are aware of and – if aware - would be content with the effect of DEPs on their trading behaviour and outcomes. Both factors would be relevant to an assessment of consumer harm arising from DEPs.

The Consumer Duty, (FCA, 2022b) came into force for open products on 31 July 2023, and will come into force for closed products on 31 July 2024. The Duty consists of a set of outcomes-focused rules which compel firms to act to deliver good outcomes for retail customers. It contains an expectation that firms avoid “designing features which exploit the behavioural biases of consumers" and a requirement that product manufacturers "undertake appropriate testing of their products to ensure they meet the needs, characteristics and objectives of an identified target market" (Financial Conduct Authority, 2022b). In addition to our immediate findings - on the effect of DEPs on consumer trading behaviour - in this research note, we hope that this research will prove instructive to all firms conducting their own testing on the effect of design features on consumer outcomes, in light of the Consumer Duty.

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Annex 1: Price simulation

The price changes of the financial instruments (funds and company shares) in the trading app were designed to be unpredictable around a trend. The range of these price changes varied depending on an investment's risk score (see Table 4).

Table 4: Price variability of instruments

Investment Name	Risk Score	Price variability based on a prominent…
Funds 1, 2, 3	1 (low-risk)	stock market index
Company A, C, E	3.5 (medium-risk)	large-cap tech company
Company B, D, F	10 (high-risk)	cryptoasset

To isolate the impact of risky investments without the influence of rent-seeking behaviour, we set the expected returns for all instruments to 4% per 1-minute period, where each period represented a year's worth of returns. This was a detail not explicitly disclosed to participants but potentially inferred from past performance graphs. Price changes occurred every 5 seconds (resulting in 12 changes per period), with each periodic return distributed around the 4% market return.

To simulate realistic price changes, we collected yearly returns data from prominent high, medium, and low-risk investments. We calculated the 10^{th} and 90^{th} percentile of returns for each investment over the last 40 years, or since the investment's inception if available for a shorter duration. The difference in natural logarithms of returns yielded a range in log returns for each investment, which we then normalised by dividing by the approximate standard deviation of the highest-risk investment.

Subsequently, using this implied standard deviation of each investment and the natural logarithm of the expected market growth rate (4%), we took a random draw from the normal cumulative distribution. This result was transformed back to a percentage change by calculating the exponential, which we then multiplied with the previous price of the investment (all starting at 100 experimental pounds), raised to the power of 1/12 to account for each price change representing one month of returns. The updated price of each investment was displayed to the nearest integer.

Ultimately, due to the unpredictable nature of price changes and the 2% fee per trade, the optimal strategy—regardless of treatment assignment—involved investing all available funds in financial instruments aligning with one's risk tolerance at the experiment's outset and holding those investments for its duration.

Annex 2: Covariates and sample

Covariates

The demographic, selected vulnerability, and experimental variables we collected (at the end of the experiment) are set out in Table 5. We controlled for all these variables in our regressions with covariates, except the amended PGSI score (Ferris & Wynne, 2001). That's because, given its length of 9 questions, we only had 40% of our participants answer the amended Problem Gambling Severity Index (PGSI) score questions. We conducted subgroup analysis with 6 of these variables. When doing so, we re-grouped the variables into two levels for ease of interpretation.

Table 5: Covariates

Variable	Main analysis (levels)	Subgroup analysis (levels)
Demographic variables		
Gender	male, female, non-binary, prefer not to say	male, female
Age	18-24, 25-34, 35-44, 45-54, 55+	18-34, 35+
Income	£0 - £25k, £25k - £50k, £50k+	£0 - £25k, £25k+
Education	university-level postgraduate education (Master/PhD or similar), university-level undergraduate education (Bachelor or similar), technical/vocational education beyond secondary school, A-levels, GCSEs, less than GCSEs, prefer not to say	NA
Employment status	full-time employed, part-time employed, temporary employment, self-employed, unemployed, retired, student, and other	NA
Trading app user	yes, no	NA
Selected vulnerability variables		
Financial literacy	low financial literacy (0/3, 1/3), medium financial literacy (2/3), high financial literacy (3/3)	low financial literacy, medium/high financial literacy
Financial resilience	low financial resilience, high financial resilience	low financial resilience, high financial resilience
Amended PGSI score	NA	No-risk or low-risk gambling behaviours, moderate or high-risk gambling behaviours
Experimental variables		
Mobile phone for experiment	yes, no	NA

Description of selected vulnerability variables

Our financial literacy measure is the “Big Three” (Lusardi & Mitchell, 2011; Lusardi & Mitchell, 2011a). The Big Three questions relate to assessing understanding of interest rates and compound interest, knowledge about inflation and its impact on purchasing power, and understanding of risk and the importance of diversifying investments. Low financial literacy we take to be answering 0 or 1 questions correctly, medium financial literacy we take as answering 2 correctly and high financial literacy we take as answering all questions correctly.

Our measure for financial resilience was based on the combination of answers to two different questions. Firstly, in the last year how often one’s money has been left over at the end of the month, on a scale from 1-5 (from “never” to “always”). Secondly, how long one’s household could make ends meet if the main source of income coming into the household was lost, on a 6 points scale (from “Less than one week” to “Twelve months or more”). Any cumulative score of 7 or above is marked as high financial resilience, a score lower than 7 is marked as low financial resilience.

A final measure we collected from some participants was an amended version of the Problem Gambling Severity Index (PGSI) score. The PGSI (Ferris & Wynne, 2001) is a scale to measure gambling-like behaviours that is used frequently in the gambling literature (Gambling Commission, 2023; Scottish Government, 2022; NHS, 2023. It consists of nine questions, such as ‘have you gambled more than you can really afford to lose?’. To each question, participants can answer: never (score = 0), sometimes (score = 1), most of the time (score = 2), or always (score = 3). A score of 0 indicates a ‘non-problem gambler’; 1 or 2 a ‘low-risk gambler’; 3 - 7 a ‘moderate-risk gambler’; 8 or more a ‘problem gambler’. We amended this scale to replace mentions of gambling with investment, for example, ‘have you invested more than you can really afford to lose?’. We included these questions in the experiment due to concerns raised in Hayes et al. (2022) about the relationship between DEPs and problem gambling/investing behaviour.

Table 6: Sample description (selected characteristics)

	Control	Flashing prices	Push notifications	Trader leaderboard	Points & prize draw	Overall
Observations	1,768	1,831	1,859	1,783	1,899	9,140
Income (%)						
£0k-£25k	40.2	41.1	39.6	40.9	39.4	40.2
£25k-£50k	39.8	38.6	43.0	42.9	41.1	41.1
£50k+	14.4	15.7	12.8	12.1	15.0	14.0
Age (%)						
18-24	13.3	10.5	11.5	13.1	10.8	11.8
25-34	32.9	32.9	33.0	31.9	32.3	32.6
35-44	24.7	27.1	26.6	26.2	26.0	26.1
45-54	15.5	15.6	15.8	15.4	16.7	15.8
55+	13.6	13.9	13.1	13.4	14.2	13.6
Gender (%)						
Female	49.0	50.1	49.2	47.7	48.0	48.8
Financial resilience (%)						
Low	34.8	35.4	35.6	37.4	36.6	36.0
Financial literacy (%)						
Low	13.2	14.4	12.4	13.0	11.9	13.0
Medium	31.6	31.9	30.7	30.4	31.4	31.2
Employment status (%)						
Full-time employed	59.0	60.3	59.0	59	59.2	59.3
Unemployed	6.4	6.5	6.3	6.7	5.1	6.2
Student	5.8	4.9	5.0	5.7	5.5	5.3
Highest level of education (%)						
GCSEs	9.4	9.2	10.5	10.2	9.8	9.8
A-levels	15.9	15.3	14.9	16.7	16.4	15.8
University-level degree	42.0	44.9	42.9	40.9	40.1	42.2
Trading app user (%)	48.2	48.6	49.8	49.7	50.9	49.5
Experiment completed on mobile (%)	38.8	39.3	38.7	40.8	39.3	39.4

Annex 3: Regression results

Table 7: Trading frequency

	Trading frequency: The number of trades made throughout the experiment	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-0.008 (0.371)	-0.054 (0.365)
Push notifications	1.456*** (0.388)	1.402*** (0.382)
Trader leaderboard	0.563 (0.381)	0.559 (0.376)
Points & prize draw	1.626*** (0.388)	1.711*** (0.384)
Income (ref: £0k-£25k)		
£25k-£50k		0.364 (0.331)
£50k+		0.890 (0.464)
Prefer not to say		0.459 (0.605)
Age (ref: 18-24)		
25-34		-2.155*** (0.543)
35-44		-3.644*** (0.554)
45-54		-4.202*** (0.584)
55+		-6.238*** (0.611)
Gender (ref: Male)		
Female		2.108*** (0.263)
Non-binary		0.903 (1.477)
Prefer not to say		0.868 (2.026)
Financial resilience (ref: Low)		
High financial resilience		-0.350 (0.270)
Financial literacy (ref: Low)		
Medium financial literacy		0.135 (0.408)
High financial literacy		-0.403 (0.404)
Trading app user		0.111 (0.258)
Mobile		-1.393*** (0.252)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
Log Likelihood	-33,285.000	-33,127.310
theta	1.672*** (0.027)	1.736*** (0.028)
Akaike Inf. Crit.	66,580.010	66,320.610

Note: *p<0.05; **p<0.01; ***p<0.001
Those Coefficients that are significant at p<0.001 are trivially significant at p<0.0125 (Bonferroni correction)
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 8: Shares bought

	Shares bought:	
	The number of total shares bought throughout the experiment	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	3.358 (2.922)	3.558 (2.909)
Push notifications	11.387*** (2.806)	11.565*** (2.778)
Trader leaderboard	8.572** (2.924)	8.011** (2.911)
Points & prize draw	9.785*** (2.880)	9.269** (2.847)
Income (ref: £0k-£25k)		
£25k-£50k		5.066* (2.499)
£50k+		11.209** (3.614)
Prefer not to say		5.531 (4.311)
Age (ref: 18-24)		
25-34		4.011 (3.536)
35-44		3.159 (3.704)
45-54		5.623 (4.102)
55+		-9.616* (4.282)
Gender (ref: Male)		
Female		-24.536*** (1.992)
Non-binary		-14.783 (8.678)
Prefer not to say		-21.607 (17.648)
Financial resilience (ref: Low)		
High financial resilience		-2.982 (2.019)
Financial literacy (ref: Low)		
Medium financial literacy		0.553 (2.990)
High financial literacy		0.834 (2.968)
Trading app user		0.124 (1.999)
Mobile		1.349 (2.022)
Constant	150.420*** (1.893)	181.338*** (17.432)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.002	0.030
Adjusted R^2	0.002	0.027
Residual Std. Error	90.826 (df = 9135)	89.692 (df = 9107)
F Statistic	5.000*** (df = 4; 9135)	8.781*** (df = 32; 9107)

Note: *p<0.05; **p<0.01; ***p<0.001
Heteroskedasticity robust standard errors in brackets

Table 9: Investment risk (final portfolio)

	Investment risk - final portfolio: The proportion (0-1) of shares owned that were in the riskiest products (risk score = 10) at the end of trading			
	(1) NA = 0	(2) NA = 0	(3) NA excluded	(4) NA excluded
Treatment (ref: Control)				
Flashing prices	-0.004 (0.010)	-0.004 (0.010)	-0.003 (0.011)	-0.003 (0.011)
Push notifications	0.016 (0.010)	0.016 (0.010)	0.016 (0.011)	0.016 (0.011)
Trader leaderboard	0.020 (0.011)	0.019 (0.011)	0.011 (0.011)	0.009 (0.011)
Points & prize draw	0.016 (0.010)	0.015 (0.010)	0.013 (0.011)	0.012 (0.011)
Income (ref: £0k-£25k)				
£25k-£50k		0.010 (0.009)		0.014 (0.010)
£50k+		0.022 (0.012)		0.028* (0.013)
Prefer not to say		0.001 (0.016)		0.003 (0.017)
Age (ref: 18-24)				
25-34		0.004 (0.013)		0.008 (0.014)
35-44		-0.015 (0.013)		-0.012 (0.014)
45-54		0.002 (0.014)		0.004 (0.015)
55+		-0.029 (0.016)		-0.033 (0.017)
Gender (ref: Male)				
Female		-0.016* (0.007)		-0.034*** (0.008)
Non-binary		-0.040 (0.039)		-0.046 (0.043)
Prefer not to say		0.013 (0.057)		-0.018 (0.059)
Financial resilience (ref: Low)				
High financial resilience		-0.011 (0.007)		-0.017* (0.008)
Financial literacy (ref: Low)				
Medium financial literacy		-0.008 (0.011)		-0.005 (0.012)
High financial literacy		0.006 (0.011)		-0.002 (0.012)
Trading app user		-0.003 (0.007)		-0.002 (0.008)
Mobile		0.002 (0.007)		0.002 (0.008)
Employment status	No	Yes	No	Yes
Level of education	No	Yes	No	Yes
Observations	9,140	9,140	8,419	8,419
R^2	0.001	0.006	0.001	0.009
Log Likelihood	18,224.870	18,244.160	13,999.480	14,031.000

Note: *p<0.05; **p<0.01; ***p<0.001
Those Coefficients that are significant at p<0.001 are trivially significant at p<0.0125 (Bonferroni correction)
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation. Constants are not displayed as there are no AMEs associated with them.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n-1) + 0.5)/n$, where n is the sample size (Smithson & Verkuilen, 2006).

This result is robust to our treatment of missing data, which arises due to some participants (around 8%) trading out of all investments prior to the end of trading. Participants that trade out of all investments, would have 0 total shares in their portfolio and by extension 0 total shares that are high-risk. Regardless of whether we include that data and set the value of investment risk as 0, or exclude the missing data altogether, the effect of our treatments is insignificant.

Table 10: Investment risk (trades made)

	Investment risk - trades made	
	The proportion (0-1) of trades made throughout the experiment that were in the riskiest investments (risk score = 10)	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-0.006 (0.010)	-0.005 (0.010)
Push notifications	0.035*** (0.010)	0.036*** (0.010)
Trader leaderboard	0.018 (0.010)	0.018 (0.010)
Points & prize draw	0.020* (0.010)	0.020* (0.010)
Income (ref: £0k-£25k)		
£25k-£50k		0.007 (0.008)
£50k+		0.025* (0.012)
Prefer not to say		0.006 (0.015)
Age (ref: 18-24)		
25-34		-0.007 (0.012)
35-44		-0.033** (0.012)
45-54		-0.006 (0.014)
55+		-0.042** (0.015)
Gender (ref: Male)		
Female		-0.019** (0.007)
Non-binary		-0.051 (0.036)
Prefer not to say		-0.062 (0.048)
Financial resilience (ref: Low)		
High financial resilience		-0.014* (0.007)
Financial literacy (ref: Low)		
Medium financial literacy		0.0001 (0.010)
High financial literacy		0.009 (0.010)
Trading app user		0.002 (0.007)
Mobile		0.009 (0.007)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.002	0.008
Log Likelihood	5,766.987	5,805.519

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation. Constants are not displayed as there are no AMEs associated with them.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n - 1) + 0.5)/n$, where n is the sample size (Smithson & Verkuilen, 2006).

Table 11: Investment risk (shares bought)

	Investment risk - shares bought	
	The proportion (0-1) of total shares bought throughout the experiment that were in the riskiest investments (risk score = 10)	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-0.005 (0.010)	-0.004 (0.009)
Push notifications	0.030** (0.010)	0.031** (0.010)
Trader leaderboard	0.020* (0.010)	0.020* (0.010)
Points & prize draw	0.017 (0.010)	0.017 (0.010)
Income (ref: £0k-£25k)		
£25k-£50k		0.007 (0.008)
£50k+		0.023* (0.012)
Prefer not to say		0.006 (0.015)
Age (ref: 18-24)		
25-34		-0.005 (0.012)
35-44		-0.028* (0.012)
45-54		-0.0004 (0.014)
55+		-0.033* (0.015)
Gender (ref: Male)		
Female		-0.024*** (0.007)
Non-binary		-0.062 (0.035)
Prefer not to say		-0.058 (0.048)
Financial resilience (ref: Low)		
High financial resilience		-0.014* (0.007)
Financial literacy (ref: Low)		
Medium financial literacy		-0.004 (0.010)
High financial literacy		0.002 (0.010)
Trading app user		0.003 (0.007)
Mobile		0.010 (0.007)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.002	0.009
Log Likelihood	6,970.487	7,007.811

Note: *p<0.05; **p<0.01; ***p<0.001
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n - 1) + 0.5)/n$, where n is the sample size (Smithson & Verkuilen, 2006).

Table 12: Diversification

	Diversification: The extent to which the portfolio at the end of trading is diversified (0-1).			
	(1) NA = 1	(2) NA = 1	(3) NA excluded	(4) NA excluded
Treatment (ref: Control)				
Flashing prices	-0.008 (0.011)	-0.007 (0.011)	-0.014 (0.011)	-0.013 (0.011)
Push notifications	0.001 (0.011)	0.0003 (0.011)	0.007 (0.011)	0.006 (0.011)
Trader leaderboard	-0.004 (0.011)	-0.002 (0.011)	0.018 (0.011)	0.021 (0.011)
Points & prize draw	0.006 (0.011)	0.007 (0.011)	0.018 (0.011)	0.020 (0.011)
Income (ref: £0k-£25k)				
£25k-£50k		-0.005 (0.010)		-0.009 (0.010)
£50k+		0.006 (0.013)		0.004 (0.013)
Prefer not to say		0.002 (0.018)		-0.003 (0.018)
Age (ref: 18-24)				
25-34		-0.020 (0.013)		-0.033^{*} (0.014)
35-44		-0.042^{**} (0.014)		-0.064^{***} (0.014)
45-54		-0.048^{**} (0.015)		-0.062^{***} (0.016)
55+		-0.087^{***} (0.017)		-0.110^{***} (0.017)
Gender (ref: Male)				
Female		0.026^{***} (0.008)		0.057^{***} (0.008)
Non-binary		0.088^{*} (0.043)		0.108^{*} (0.045)
Prefer not to say		-0.026 (0.059)		0.027 (0.059)
Financial resilience (ref: Low)				
High financial resilience		-0.002 (0.008)		0.002 (0.008)
Financial literacy (ref: Low)				
Medium financial literacy		0.016 (0.012)		0.011 (0.012)
High financial literacy		0.025^{*} (0.012)		0.044^{***} (0.012)
Trading app user		-0.001 (0.008)		-0.004 (0.008)
Mobile		-0.013 (0.008)		-0.015^{*} (0.007)
Employment status	No	Yes	No	Yes
Level of education	No	Yes	No	Yes
Observations	9,140	9,140	8,419	8,419
R^2	0.0002	0.010	0.001	0.023
Log Likelihood	11,292.950	11,338.050	7,713.382	7,808.164

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n-1) + 0.5)/n$, where n is the sample size (Smithson, & Verkuilen, 2006).

This result is robust to our treatment of missing data, which arises due to some participants (around 8%) trading out of all investments prior to the end of trading. Participants that trade out of all investments, would have 0 total shares in their portfolio. Regardless of whether we include that data and set the value of the diversification score as 1 or exclude the missing data altogether, the effect of our treatments is insignificant.

Table 13: Engagement with alternative task

	Engagement – alternative task:	
	The number of transcriptions completed in the task offered as an alternative to trading	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-1.149** (0.417)	-0.990* (0.397)
Push notifications	-3.829*** (0.404)	-3.770*** (0.385)
Trader leaderboard	-2.195*** (0.426)	-2.041*** (0.407)
Points & prize draw	-3.087*** (0.416)	-2.828*** (0.398)
Income (ref: £0k-£25k)		
£25k-£50k		-0.756* (0.330)
£50k+		-0.785 (0.478)
Prefer not to say		-0.946 (0.632)
Age (ref: 18-24)		
25-34		-0.925 (0.531)
35-44		-3.523*** (0.539)
45-54		-6.718*** (0.566)
55+		-8.436*** (0.609)
Gender (ref: Male)		
Female		0.708** (0.271)
Non-binary		1.188 (1.596)
Prefer not to say		1.373 (2.355)
Financial resilience (ref: Low)		
High financial resilience		0.881** (0.269)
Financial literacy (ref: Low)		
Medium financial literacy		0.136 (0.370)
High financial literacy		0.914* (0.376)
Trading app user		-0.007 (0.268)
Mobile		-4.901*** (0.251)
Constant	15.135*** (0.299)	19.933*** (1.538)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.012	0.104
Adjusted R^2	0.011	0.101
Residual Std. Error	12.430 (df = 9135)	11.855 (df = 9107)
F Statistic	27.299*** (df = 4; 9135)	33.020*** (df = 32; 9107)

Note: *p<0.05; **p<0.01; ***p<0.001
Heteroskedasticity robust standard errors in brackets

Table 14: Engagement with key information

	Engagement - key information	
	The number of times information on stocks (with past performance and risk score) was opened	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-1.109^{*} (0.526)	-1.098^{*} (0.515)
Push notifications	-0.348 (0.539)	-0.517 (0.525)
Trader leaderboard	0.212 (0.557)	0.076 (0.543)
Points & prize draw	0.775 (0.560)	0.952 (0.552)
Income (ref: £0k-£25k)		
£25k-£50k		0.053 (0.454)
£50k+		1.060 (0.652)
Prefer not to say		1.195 (0.887)
Age (ref: 18-24)		
25-34		-1.553^{*} (0.777)
35-44		-3.450^{***} (0.785)
45-54		-4.765^{***} (0.812)
55+		-6.514^{***} (0.841)
Gender (ref: Male)		
Female		-0.329 (0.361)
Non-binary		4.820 (2.871)
Prefer not to say		1.887 (3.279)
Financial resilience (ref: Low)		
High financial resilience		1.763^{***} (0.357)
Financial literacy (ref: Low)		
Medium financial literacy		3.849^{***} (0.406)
High financial literacy		6.232^{***} (0.418)
Trading app user		-0.469 (0.358)
Mobile		0.339 (0.358)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
Log Likelihood	-31,888.210	-31,675.790
theta	0.590^{***} (0.010)	0.626^{***} (0.011)
Akaike Inf. Crit.	63,786.420	63,417.580

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Coefficients are transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 15: Amount uninvested

	Amount uninvested:	
	The amount not invested at the end of the experiment, as a percentage of the starting endowment.	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	0.674 (1.341)	0.750 (1.337)
Push notifications	2.833* (1.338)	2.994* (1.338)
Trader leaderboard	-2.763* (1.282)	-2.666* (1.283)
Points & prize draw	-1.410 (1.293)	-1.368 (1.294)
Income (ref: £0k-£25k)		
£25k-£50k		2.601* (1.107)
£50k+		3.572* (1.546)
Prefer not to say		3.687 (2.040)
Age (ref: 18-24)		
25-34		-1.428 (1.628)
35-44		-1.942 (1.697)
45-54		-1.083 (1.825)
55+		-2.269 (2.079)
Gender (ref: Male)		
Female		-4.198*** (0.893)
Non-binary		5.720 (5.521)
Prefer not to say		-13.788* (5.425)
Financial resilience (ref: Low)		
High financial resilience		-0.957 (0.916)
Financial literacy (ref: Low)		
Medium financial literacy		0.663 (1.396)
High financial literacy		-3.540** (1.366)
Trading app user		0.128 (0.879)
Mobile		-1.085 (0.885)
Constant	26.197*** (0.946)	36.057*** (6.653)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.002	0.011
Adjusted R^2	0.002	0.008
Residual Std. Error	39.289 (df = 9135)	39.170 (df = 9107)
F Statistic	5.345*** (df = 4; 9135)	3.284*** (df = 32; 9107)

Note: *p<0.05; **p<0.01; ***p<0.001
Heteroskedasticity robust standard errors in brackets

Table 16: Trading earnings (by number of trades)

	Trading earnings:
	Earnings made from trading, as a percentage change in comparison to the starting endowment
Trading frequency	-0.110*** (0.028)
Constant	23.615*** (0.574)
Observations	9,140
R^2	0.002
Adjusted R^2	0.002
Residual Std. Error	28.537 (df = 9138)
F Statistic	18.936*** (df = 1; 9138)

Note : *p<0.05; **p<0.01; ***p<0.001
Heteroskedasticity robust standard errors in brackets

Table 17: Trading earnings

	Trading earnings: Earnings made from trading, as a percentage change in comparison to the starting endowment	
	(1)	(2)
Treatment (ref: Control)		
Flashing prices	-1.036 (0.934)	-1.014 (0.935)
Push notifications	-1.296 (0.954)	-1.208 (0.956)
Trader leaderboard	-0.013 (0.944)	0.037 (0.940)
Points & prize draw	0.990 (0.957)	1.029 (0.956)
Income (ref: £0k-£25k)		
£25k-£50k		-1.340 (0.836)
£50k+		-0.952 (1.162)
Prefer not to say		0.270 (1.536)
Age (ref: 18-24)		
25-34		0.163 (0.998)
35-44		-0.226 (1.064)
45-54		1.404 (1.236)
55+		0.788 (1.383)
Gender (ref: Male)		
Female		1.852** (0.663)
Non-binary		-0.287 (2.191)
Prefer not to say		-3.293 (3.422)
Financial resilience (ref: Low)		
High financial resilience		1.385* (0.648)
Financial literacy (ref: Low)		
Medium financial literacy		-1.467 (1.002)
High financial literacy		0.015 (1.007)
Trading app user		0.071 (0.627)
Mobile		0.995 (0.649)
Constant	22.313*** (0.673)	22.506*** (4.745)
Employment status	No	Yes
Level of education	No	Yes
Observations	9,140	9,140
R^2	0.001	0.005
Adjusted R^2	0.0004	0.001
Residual Std. Error	28.559 (df = 9135)	28.548 (df = 9107)
F Statistic	1.930 (df = 4; 9135)	1.339 (df = 32; 9107)

Note: *p<0.05; **p<0.01; ***p<0.001
Heteroskedasticity robust standard errors in brackets

Table 18: Subgroup analysis A (trading frequency)

	Trading frequency: The number of trades made throughout the experiment		
	(1)	(2)	(3)
Treatment (ref: Control)			
Flashing prices	0.151* (0.074)	0.033 (0.046)	0.009 (0.103)
Push notifications	0.210** (0.076)	0.103* (0.046)	0.136 (0.101)
Trader leaderboard	0.247** (0.076)	0.026 (0.046)	-0.079 (0.107)
Points & prize draw	0.247** (0.076)	0.139** (0.045)	0.072 (0.097)
Financial literacy (ref: Low)			
Medium / high financial literacy	0.081 (0.058)		
Interaction term (ref: treatment[i] * Low lit)			
Flashing prices * Medium / high financial lit.	-0.176* (0.079)		
Push notifications * Medium / high financial lit.	-0.124 (0.081)		
Trader leaderboard * Medium / high financial lit.	-0.238** (0.081)		
Points & prize draw * Medium / high financial lit.	-0.153 (0.081)		
Financial resilience (ref: Low)			
High financial resilience		-0.035 (0.041)	
Interaction term (ref: treatment[i] * Low res)			
Flashing prices * High financial res.		-0.053 (0.057)	
Push notifications * High financial res.		-0.003 (0.057)	
Trader leaderboard * High financial res.		0.022 (0.057)	
Points & prize draw * High financial res.		-0.042 (0.056)	
Gambling behaviour (ref: medium / high)			
No / low gambling behaviour			-0.043 (0.078)
Interaction term (ref: treatment[i] * medium / high gambling beh.)			
Flashing prices * No / low gambling beh.			-0.040 (0.112)
Push notifications * No / low gambling beh.			0.003 (0.110)
Trader leaderboard * No / low gambling beh.			0.143 (0.116)
Points & prize draw * No / low gambling beh.			0.017 (0.106)
Constant	2.537*** (0.054)	2.631*** (0.033)	2.642*** (0.072)
Observations	9,140	9,140	3,825
Log Likelihood	-33,277.540	-33,279.750	-13,851.420
theta	1.675*** (0.027)	1.675*** (0.027)	1.820*** (0.046)
Akaike Inf. Crit.	66,575.080	66,579.490	27,722.850

Note: *$p<0.05$; **$p<0.01$; ***$p<0.001$
Coefficients have not been transformed to AMEs.

Table 19: Subgroup analysis B (trading frequency)

	Trading frequency: The number of trades made throughout the experiment		
	(1)	(2)	(3)
Treatment (ref: Control)			
Flashing prices	0.030 (0.039)	0.060 (0.040)	-0.069 (0.043)
Push notifications	0.156*** (0.039)	0.153*** (0.040)	0.084* (0.043)
Trader leaderboard	0.090* (0.039)	0.075 (0.040)	-0.008 (0.043)
Points & prize draw	0.166*** (0.039)	0.126** (0.040)	0.067 (0.043)
Gender (ref: Female)			
Male	-0.050 (0.039)		
Interaction term (ref: treatment[i] * Female)			
Flashing prices * Male	-0.066 (0.055)		
Push notifications * Male	-0.112* (0.055)		
Trader leaderboard * Male	-0.105 (0.055)		
Points & prize draw * Male	-0.107* (0.054)		
Age (ref: 18-34)			
35+		-0.141*** (0.039)	
Interaction term (ref: treatment[i] * 18-34)			
Flashing prices * 35+		-0.109* (0.055)	
Push notifications * 35+		-0.096 (0.054)	
Trader leaderboard * 35+		-0.064 (0.055)	
Points & prize draw * 35+		-0.017 (0.054)	
Income (ref: £0k-£25k)			
£25k+			-0.069 (0.041)
Interaction term (ref: treatment[i] * £0k-£25k)			
Flashing prices * £25k+			0.103 (0.057)
Push notifications * £25k+			0.022 (0.056)
Trader leaderboard * £25k+			0.071 (0.057)
Points & prize draw * £25k+			0.069 (0.056)
Constant	2.633*** (0.028)	2.681*** (0.028)	2.652*** (0.031)
Observations	9,044	9,140	8,706
Log Likelihood	-32,902.960	-33,214.840	-31,688.310
theta	1.680*** (0.027)	1.700*** (0.028)	1.676*** (0.028)
Akaike Inf. Crit.	65,825.920	66,449.680	63,396.630

Note: *p<0.05; **p<0.01; ***p<0.001
Coefficients have not been transformed to AMEs.

Table 20: Subgroup analysis C (trading frequency)

	Trading frequency: The number of trades made throughout the experiment		
	(1)	(2)	(3)
Treatment (ref: Control)			
Flashing prices	0.147* (0.074)	0.030 (0.038)	0.041 (0.041)
Push notifications	0.194* (0.076)	0.155*** (0.038)	0.040 (0.040)
Trader leaderboard	0.237** (0.076)	0.092* (0.039)	0.040 (0.040)
Points & prize draw	0.232** (0.076)	0.175*** (0.038)	0.040 (0.040)
Financial literacy (ref: Low)			
Medium / high financial literacy	0.127* (0.058)	-0.047 (0.039)	0.039 (0.039)
Interaction term (ref: treatment[i] * Low lit)			
Flashing prices * Medium / high financial lit.	-0.173* (0.079)		
Push notifications * Medium / high financial lit.	-0.109 (0.081)		
Trader leaderboard * Medium / high financial lit.	-0.231** (0.081)		
Points & prize draw * Medium / high financial lit.	-0.132 (0.081)		
Gender (ref: Female)			
Male	-0.128*** (0.017)	-0.005 (0.026)	0.026 (0.026)
Interaction term (ref: treatment[i] * Female)			
Flashing prices * Male		-0.065 (0.054)	
Push notifications * Male		-0.111* (0.054)	
Trader leaderboard * Male		-0.109* (0.055)	
Points & prize draw * Male		-0.115* (0.054)	
Age (ref: 18-34)			
35+	-0.197*** (0.017)	-0.196*** (0.017)	0.017 (0.017)
Interaction term (ref: treatment[i] * 18-34)			
Flashing prices * 35+			0.055 (0.055)
Push notifications * 35+			0.054 (0.054)
Trader leaderboard * 35+			0.055 (0.055)
Points & prize draw * 35+			0.054 (0.054)
Constant	2.666*** (0.054)	2.740*** (0.035)	0.036 (0.036)
Observations	9,044	9,044	9,044
Log Likelihood	-32,836.330	-32,837.530	-32,838.020
theta	1.707*** (0.028)	1.706*** (0.028)	1.706*** (0.028)
Akaike Inf. Crit.	65,696.650	65,699.050	65,700.050

Note: *p<0.05; **p<0.01; ***p<0.001
Coefficients have not been transformed to AMEs.

Table 21: Subgroup analysis A (investment risk – final portfolio)

	Investment risk - final portfolio: The proportion (0-1) of shares owned that were in the riskiest products (risk score = 10) at the end of trading		
	(1)	(2)	(3)
Treatment (ref: Control)			
Flashing prices	-0.087 (0.120)	0.002 (0.075)	-0.011 (0.177)
Push notifications	0.002 (0.124)	0.081 (0.075)	-0.106 (0.174)
Trader leaderboard	0.078 (0.124)	0.105 (0.075)	0.086 (0.183)
Points & prize draw	-0.019 (0.124)	0.126 (0.074)	-0.041 (0.167)
Financial literacy (ref: Low)			
Medium / high financial literacy	-0.053 (0.094)		
Interaction term (ref: treatment[i] * Low lit)			
Flashing prices * Medium / high financial lit.	0.079 (0.129)		
Push notifications * Medium / high financial lit.	0.077 (0.133)		
Trader leaderboard * Medium / high financial lit.	0.008 (0.133)		
Points & prize draw * Medium / high financial lit.	0.099 (0.133)		
Financial resilience (ref: Low)			
High financial resilience		0.003 (0.066)	
Interaction term (ref: treatment[i] * Low res)			
Flashing prices * High financial res.		-0.033 (0.093)	
Push notifications * High financial res.		-0.019 (0.093)	
Trader leaderboard * High financial res.		-0.031 (0.093)	
Points & prize draw * High financial res.		-0.092 (0.092)	
Gambling behaviour (ref: medium / high)			
No / low gambling behaviour			-0.182 (0.134)
Interaction term (ref: treatment[i] * medium / high gambling beh.)			
Flashing prices * No / low gambling beh.			0.009 (0.192)
Push notifications * No / low gambling beh.			0.227 (0.189)
Trader leaderboard * No / low gambling beh.			-0.020 (0.198)
Points & prize draw * No / low gambling beh.			0.162 (0.182)
Constant	-0.496*** (0.087)	-0.544*** (0.054)	-0.360** (0.123)
Observations	9,140	9,140	3,825
R^2	0.001	0.001	0.003
Log Likelihood	18,225.330	18,226.060	7,576.668

Note: *$p<0.05$; **$p<0.01$; ***$p<0.001$
Coefficients have not been transformed to AMEs.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n - 1) + 0.5)/n$, where n is the sample size (Smithson & Verkuilen, 2006).

Table 22: Subgroup analysis B (investment risk – final portfolio)

	Investment risk - final portfolio: The proportion (0-1) of shares owned that were in the riskiest products (risk score = 10) at the end of trading		
	(1)	(2)	(3)
Treatment (ref: Control)			
Flashing prices	0.004 (0.063)	0.108 (0.066)	0.066 (0.069)
Push notifications	0.107 (0.063)	0.198^{**} (0.066)	0.118 (0.070)
Trader leaderboard	0.114 (0.064)	0.208^{**} (0.066)	0.147^{*} (0.070)
Points & prize draw	0.096 (0.063)	0.185^{**} (0.066)	0.111 (0.070)
Gender (ref: Female)			
Male	0.127^{*} (0.064)		
Interaction term (ref: treatment[i] * Female)			
Flashing prices * Male	-0.036 (0.089)		
Push notifications * Male	-0.078 (0.089)		
Trader leaderboard * Male	-0.060 (0.090)		
Points & prize draw * Male	-0.067 (0.089)		
Age (ref: 18-34)			
35+		0.125^{*} (0.063)	
Interaction term (ref: treatment[i] * 18-34)			
Flashing prices * 35+		-0.230^{**} (0.089)	
Push notifications * 35+		-0.237^{**} (0.089)	
Trader leaderboard * 35+		-0.227^{*} (0.090)	
Points & prize draw * 35+		-0.214^{*} (0.089)	
Income (ref: £0k-£25k)			
£25k+			0.122 (0.066)
Interaction term (ref: treatment[i] * £0k-£25k)			
Flashing prices * £25k+			-0.136 (0.092)
Push notifications * £25k+			-0.100 (0.092)
Trader leaderboard * £25k+			-0.122 (0.093)
Points & prize draw * £25k+			-0.075 (0.092)
Constant	-0.604^{***} (0.045)	-0.609^{***} (0.047)	-0.609^{***} (0.050)
Observations	9,044	9,140	8,706
R^2	0.002	0.003	0.002
Log Likelihood	18,064.190	18,232.110	17,341.300

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Coefficients have not been transformed to AMEs.

To enable us to use beta regression which requires an outcome variable strictly between 0 and 1, we use the following transformation on the outcome variable (y), $(y \cdot (n - 1) + 0.5)/n$, where n is the sample size (Smithson & Verkuilen, 2006).

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