Financial Conduct Authority

66

Occasional Paper

April 2025

Playing the market: a behavioural data analysis of digital engagement practices and investment outcomes

John Gathergood, Cameron Gilchrist, Mark D. Griffiths, Lucy Hayes, Emily Morris, Stephen O'Neill, Jesal D. Sheth & Neil Stewart

FCA occasional papers in financial regulation

The FCA occasional papers

The FCA is committed to encouraging debate on all aspects of financial regulation and to creating rigorous evidence to support its decision-making. To facilitate this, we publish a series of Occasional Papers, extending across economics and other disciplines.

The main factor in accepting papers is that they should make substantial contributions to knowledge and understanding of financial regulation. If you want to contribute to this series or comment on these papers, please contact David Stallibrass (david.stallibrass@fca.org.uk).

Disclaimer

Occasional Papers contribute to the work of the FCA by providing rigorous research results and stimulating debate. While they may not necessarily represent the position of the FCA, they are one source of evidence that the FCA may use while discharging its functions and to inform its views. The FCA endeavours to ensure that research outputs are correct, through checks including independent referee reports, but the nature of such research and choice of research methods is a matter for the authors using their expert judgement. To the extent that Occasional Papers contain any errors or omissions, they should be attributed to the individual authors, rather than to the FCA.

Authors

John Gathergood (University of Nottingham), Cameron Gilchrist (during his time at the FCA), Jesal D. Sheth (FCA), Mark D. Griffiths (Nottingham Trent University), Lucy Hayes (FCA), Emily Morris (FCA), Stephen O’Neill (during his time at the FCA) & Neil Stewart (Warwick Business School).

Acknowledgements

We would like to thank Cameron Belton (FCA), Kieran Keohane (FCA), Cherryl Ng (FCA), Manasi Phadnis (FCA) and David Stallibrass (FCA) for their contributions to this paper.

All our publications are available to download from www.fca.org.uk. If you would like to receive this paper in an alternative format, please call 020 7066 9644 or email publications_graphics@fca.org.uk or write to Editorial and Digital Department, Financial Conduct Authority, 12 Endeavour Square, London E20 1JN.

Equality and diversity considerations

We have considered the equality and diversity issues that may arise from the research in this Occasional Paper. Overall, we do not consider that the research in this Occasional Paper 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.

Contents

Summary

Previous research has found that digital engagement practices (DEPs) – "elements or features designed to engage retail investors on digital platforms" (SEC, 2021) such as push notifications and prize-draws – can change consumer investment behaviour and potentially lead to poorer investment outcomes (see, for examples, experimental studies in Hayes et al., 2022; Gathergood et al., 2024). In this paper, we draw upon a large representative sample of consumer data from several trading app firms (platforms that allow users to buy and sell investment products predominantly via applications on their phones), to investigate the impact of DEPs on real consumer outcomes.

Our dataset is particularly rich as it links individual investor trading records, which covers a period of 7 months between 1 November 2021 and 30 November 2022, to their credit files obtained from a UK Credit Reference Agency (CRA). Linked CRA data was achieved for 63% of investors in the dataset, providing a large sample in which we can observe both trading behaviours and downstream credit and debt outcomes as measured in the credit file.

To explore the associations between DEPs and trading outcomes, we classify trading apps by their intensity of usage of DEPs in the consumer experience (low, medium, and high). Using this classification, we analyse the relationship between consumer exposure to DEPs and consumer outcomes.

In terms of consumer financial outcomes, we find that both realised and unrealised returns are significantly worse among consumers participating on the high DEP apps. We also find that the incidence of what we term 'large' losses - more than 2% of pro rata net income - is 4.8 percentage points higher on the high DEP apps than low DEP apps, once demographics are accounted for.

In addition, we find that when compared to users of low DEP apps, consumers of high DEP apps (and to a lesser extent, medium DEP apps) are more likely to:

- be younger and male.
- display higher levels of engagement on the app, as measured by more frequent sessions (including at night), spending more days on the app, and spending longer on the app.
- trade more frequently on the app, as measured by number of trades, portfolio turnover, day trades (opening and closing a position in the same day), and night trades (making trades between 11pm and 6am.)
- be in financial distress - but less likely to be so than the population overall.

- display ‘potentially problematic engagement’ on the app, as measured by our index which seeks to capture elevated, erratic, or concerning trading behaviour.

Our findings illustrate the association between usage of high DEP apps and adverse financial outcomes. However, the results should not be read as evidence that usage of high DEP apps *cause* adverse financial outcomes, as there may be a variety of channels linking high DEP apps and the financial circumstances of consumers. Individuals with existing financial distress and precarity may be more likely to use high DEP apps as compared to other apps. Use of high DEP apps might also be correlated with other attributes which worsen consumer outcomes, such as vulnerability or poor financial literacy. Moreover, the product offerings of high DEP apps differed to medium and low DEP apps; notably contract for difference (CFD) products and cryptoassets (which in our sample were only offered on high DEP apps) appear to play a substantial role in investment outcomes.

Disentangling the relative causal effects of DEPs, investor characteristics and product choices on consumer investment outcomes is a question for further research. Under the Consumer Duty’s (FCA, 2022a; FCA, 2022b) obligation that firms “act to deliver good outcomes”, our research reiterates the importance of ongoing evaluation of consumers investment behaviours and outcomes.

1 Overview

Purpose

This paper primarily examines the relationship between consumer investment outcomes and digital engagement practices (DEPs) on trading apps. DEPs – "elements or features designed to engage retail investors on digital platforms" (SEC, 2021) – is a term that incorporates gamification - "the use of game design elements in non-game contexts" (Deterding et al., 2011) - and other attention-grabbing attributes. Examples of DEPs include positive reinforcement (e.g. falling confetti); frequent push notifications; trader leaderboards; and defaults on leverage or investment amounts (Hayes et al., 2022).

This research – which we believe to be the first publicly available analysis comparing retail investors across multiple trading apps in the UK – builds on our previous investment research, which relied on survey and online experiment approaches (Gathergood et al., 2024; Hayes et al., 2022).

In the UK, 21.2 million people (39% of all adults) hold some form of investment (FCA, 2025). Investment provides an important channel through which people can increase their wealth and save for later life (FCA, 2023b). We are interested in the relationship between consumer trading behaviour and DEPs because some new apps make intensive usage of DEPs, and these apps have grown in popularity in recent years (FCA, 2021b; 2024). In addition, research has indicated that DEPs may influence consumer investment behaviours and lead to potentially poorer outcomes (e.g., Broihanne, 2023; Gathergood et al., 2024; Hayes et al., 2022; Ontario Securities Commission [OSC], 2022).

The FCA has previously raised concerns about potential poor outcomes linked to DEPs and trading app design (FCA, 2022c, 2024). These concerns are particularly relevant within the Consumer Duty context (FCA, 2022a), a set of outcomes-focused rules which require firms to act to deliver good outcomes for retail customers.

Our primary hypothesis in this research is that greater prevalence of DEPs on an app will be associated with worse consumer outcomes. The first proposed mechanism for this is that DEPs could be influencing consumers to display 'potentially problematic engagement' (PPE) behaviours such as excessive trading frequency, which in turn results in poorer returns. The second proposed mechanism is that DEPs could be influencing consumers to take on investments that are beyond their risk appetite, potentially leading to unexpectedly sharp losses.

Key findings

To explore the association between DEP prevalence and consumer investment outcomes, we collected trading data from several trading apps. For our analysis, we separated apps into three groups based on the number of DEPs present on the platform:

1. Low number of DEPs (zero or one)
2. Medium number of DEPs (two to four)
3. High number of DEPs (five or more)

Importantly, the trading apps in our sample differ in more dimensions than the extent to which they feature DEPs. Consequently, we do not present our analysis as representing a causal relationship between DEPs and trading behaviours or outcomes. One such dimension is product offerings - not all apps offer cryptoassets or contracts for differences (CFDs), for instance. Where possible, we make additional comparisons between investors that did and did not use cryptoassets and CFDs.

The user bases of the different apps are also likely to be different. In our regression analysis, we accounted for observable demographic factors such as age, gender, and income. However, there may also be unobservable differences that can affect both choice of app and investment outcomes, such as a person's vulnerability, attitude to risk, or motivation for investing. It may be the case that firms employing DEPs are attracting consumers who would have achieved worse returns in the absence of DEPs or for whom the DEPs are directly leading to worse returns, or a combination of both. In either case, our research suggests that firms should continue to comply with relevant Consumer Duty requirements, (FCA 2022a, 2022b) including the obligation to:

- Consider the needs, characteristics and objectives of their target market when developing and monitoring the app.
- Support consumer understanding to equip customers to make decisions that are effective, timely and informed.
- Enable and support customers to pursue their financial objectives.

Restricting our analysis to active investors - those who had a portfolio exceeding £100 at some stage in our data - we find the following:

- Consumers who use trading apps were substantially more likely to be male, young and high-income when compared to the rest of the population.
- Median net income and portfolio value were substantially higher on low DEP apps than high DEP apps.
- Consumers who use trading apps were more likely than the general population (as proxied by our CRA dataset) to hold credit products including mortgages,

personal loans, and motor finance. However, they were less likely to be in financial distress.

- Users of high DEP apps displayed higher levels of engagement, as measured by more frequent sessions (including at night), spending more days on the app, spending longer on the app, and making more ad hoc deposits and withdrawals.
- The median user of a high DEP app made seven times more trades than the median user of a low DEP app.
- 9% of portfolios on high DEP apps are completely undiversified, compared to 13% of low DEP apps. Looking only at portfolios worth at least £5k, these proportions fall to 4% and 3% respectively.
- Among the customer base of apps offering them, two thirds traded or held cryptoassets. For CFDs the equivalent rate was 1 in 5. In total, 38% of investors with accounts on apps offering both CFDs and cryptoassets held 90% or more of their portfolio value in these products.
- Those on the high DEP apps achieved significantly lower returns compared to those on the low DEP apps.
- Virtually all of the underperformance on high DEP apps could be attributed to trading in cryptoassets and CFDs which – in our sample of firms – were only available on high DEP apps. This could still be consistent with our underlying hypothesis, since one of the key mechanisms through which DEPs could cause harm is by encouraging users to trade in products that are beyond their risk appetite, but further research is needed to understand to what extent this is the case.
- Users of high DEP apps were almost twice as likely to show signs of potentially problematic engagement (PPE), based on an experimental measure we developed that was inspired by the literature on operationalising problem gambling measures e.g. Catania & Griffiths (2022).
- We also observe elevated levels of PPE among those who have traded CFDs and cryptoassets. To a degree this is expected due to the characteristics of these products - CFDs are short-term speculative instruments that are often traded intra-day, while cryptoassets can be traded 24 hours a day, unlike most traditional investments.
- Users showing signs of PPE tended to have poorer returns and a significantly higher rate of large losses, even accounting for the use of CFDs and cryptoassets.

2 Research context

The benefits of investing

Investment provides an important channel through which people can increase their wealth and save for later life (FCA, 2023b), and the FCA has in recent years emphasised the importance to consumers – with a suitable risk tolerance – of moving away from holding large cash balances towards investments (FCA, 2023c; Rathi, 2024).

The returns from investment are, of course, dependent on a range of factors, including asset allocation, fees, and market conditions. However, over a long enough period a time, most investors can enjoy the tendency for markets - and hence their investments - to rise in value. By example, in the ten years to January 2025, the FTSE 100 returned around 21% and the S&P500 returned around 187%. A long-term study of retail investment returns at a large discount broker from 1991 to 1996 found that the average household earned an annual return of around 16% (Barber and Odean, 2000).

The rise of the trading app

Trading apps, which allow consumers to buy and sell investment products - primarily through mobile applications - have grown substantially in popularity in recent years. In the first four months of 2021, when GameStop was leading the news (FCA 2021a), UK customers opened more than a million new accounts with four trading apps - nearly double that of all other retail investment platforms combined (FCA 2021b). In the next three years, at the same four firms, on average 70,000 new accounts were opened each month (FCA, 2024a).

These apps allow retail investors to trade in a wide variety of products, from exchange-traded funds to fractional shares to higher-risk investments such as cryptoassets and ‘contract for differences’ (CFDs). Such products are offered in an interactive interface that, alongside widespread advertising and an offer of zero-commission trading, has appealed to a wider customer base in the UK. They are usually offered on an execution-only basis, and cater primarily to self-directed investors and traders.

However, while these platforms have offered a new way for consumers to invest, the FCA (FCA, 2022c, 2024a) and other global regulators (Broihanne, 2023; European Securities and Markets Authority [ESMA], 2023; International Organisation of Securities Commissions [IOSCO], 2022, 2024; Massachusetts Securities Division, 2020; OSC, 2022; SEC, 2021) have raised concerns regarding the design features used by some trading apps and the impact they may have on investor behaviour.

Traders vs. investors?

We recognise that there is an ongoing debate surrounding the differences between 'traders' (often characterised by frequent buying and selling of assets in an attempt to capitalise on short-term market movements) and 'investors' (often characterised by infrequent buying and holding of assets in pursuit of returns over the long term). Crucially, both traders and investors operate in the same markets, and often on the same platforms. The apps in our sample will inevitably contain a mixture of both types of users (though perhaps in different proportions). This is especially true given that some individuals engage in both trading and investing. For the purposes of this paper, we use the terms interchangeably when referring to the users of these platforms.

Digital engagement practices (DEPs), sludge, and deceptive design

The features of concern 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), a definition which subsumes the concept of gamification (Deterding et al., 2011). An earlier survey (Hayes et al., 2022) gave examples of some such features: celebratory messages accompanying trades, trader leaderboards highlighting the best performing traders, and extremely frequent push notifications with price updates.

A range of academic literature has found that DEPs can affect how consumers interact with and behave on trading and investment apps (Andraszewicz et al., 2024; Arnold et al., 2022; Barber et al., 2022; Broihanne, 2023; Chapkovski et al., 2021; Elliott et al., 2023; Grant et al., 2023; Moss, 2022; OSC, 2022, 2024).

The findings from our November 2022 survey (Hayes et al., 2022) added to this literature, showing that among 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 and invest in products potentially beyond their risk appetite.

Our June 2024 online experiment (Gathergood et al., 2024) showed further that, in a sample of 9,000 consumers, DEPs (specifically push notifications and a 'points and prize draw') could cause an increase in trade frequency and riskiness of trading. Our sub-group analysis found that those with lower financial literacy increased their trading frequency by more when presented with trader leaderboard or flashing prices (Figure 1) - a concerning finding, given that we know that many new, self-directed investors are younger and possess less investing experience than the average investor (FCA, 2021a).

Figure 1. Digital engagement practices – trader leaderboard and flashing prices – as tested in Gathergood et al. (2024)

Beyond DEPs, there are other terms used to describe design features that could shape consumer choices and may be of concern. For example, deceptive design (also referred to as dark patterns), that we take to mean user interface elements which could lead consumers into taking actions which may be against their best interests (Gray, et al., 2018; Mathur et al., 2021). An example of this is when the suggested investment amount or leverage offered on an app is defaulted to an inappropriately high amount (Hayes et al., 2022). Related to this is the concept of "sludge," which refers to unnecessary and harmful barriers or frictions that unreasonably restrict a customer from acting in their interests (FCA, 2022b; Sunstein, 2019, 2022; Thaler, 2018). For example, the layout of an app could make it hard for an investor to find information, including the need to search, scroll, or click around excessively to find out about costs (ESMA, 2023). The Consumer Duty requires that, in order to support consumer understanding, information should be presented in a logical manner, making key information prominent and easy to identify (FCA 2022a, 2022b).

Importantly however, design features are not always inherently harmful for consumers - appropriate friction in a consumer journey such that it, for example, slows down consumers when investing in high-risk products can often be beneficial (Farghly et al., 2022; Gilchrist et al., 2022), and thus is required under the Consumer Duty (FCA 2022a, 2022b). Similarly, DEPs, such as badges, can be used to encourage consumers to invest in safer investments (Broihanne, 2023). Further, it may be that some DEPs, alongside advertising, play a role in attracting new investors to platforms, encouraging them to consider investment in the first place. If for these consumers the outside option to high DEP apps is, for example, online gambling (where rates of losses are far greater than investment apps, as discussed further in Annex 4) as opposed to low DEP apps, then the influence of DEPs is more nuanced. Ultimately, the key consideration is the resulting consumer outcomes that are achieved by these design features.

A question of outcomes: trading frequency, risk-taking, and potentially problematic engagement

The key concern is that DEPs may lead consumers to increase both trading frequency and risk-taking in a manner inconsistent with their objectives or risk preferences. Research has demonstrated that trading more leads to poorer financial returns (Barber & Odean, 2000, 2013; Gargano & Rossi, 2018; Shefrin & Statman 1985). This is in large part due to transaction costs and the bid-ask spread (the difference between the price at which investors can sell and buy a given asset) (Barber & Odean, 2000, 2013; Barber et al., 2014). However, it is also in part due to increased opportunity to succumb to behavioural biases such as the 'disposition effect,' which refers to the propensity to sell winning investments whilst holding losing investments (Shefrin & Statman 1985).

While some degree of risk-taking is necessary to reap the rewards of investing, there is concern that investors may not fully account for the downsides of investing in risky assets and so are not able to evaluate whether they are taking risks in line with their risk appetite, leading to unexpected or unmanageable losses. A survey commissioned by the FCA (BritainThinks, 2021) found that half of non-advised investors in high-risk, high-reward investments did not view 'losing some money' as a potential risk of investing. A more recent survey found that two in five investors had regretted purchasing a 'hyped' investment product (FCA, 2024), where 'hype' refers to an "intensive, sometimes spectacular" form of promoting something to potential buyers (FCA 2022b).

A further concern is that DEPs may be associated with problem gambling-like behaviour on trading apps. Hayes et al. (2022) – using an amended version of the Problem Gambling Severity Index (PGSI) – found that users of trading apps with more DEPs were more likely to exhibit 'at-risk of problem gambling' behaviours. The research found that 3.75% of trading app users met these criteria, approximately equal to the 4.1% of UK gamblers who meet the threshold for problem gambling (Gambling Commission, 2023). We investigated problem gambling-like behaviour, via our measure of 'potentially problematic engagement,' expanded on in Annex 4.

The Consumer Duty and its implications

Since increases in trading, risk-taking, or potentially problematic engagement has the potential to lead to poor consumer outcomes – especially if the trading behaviour of consumers is being influenced by DEPs without their knowledge – this may be of relevance to firms in light of their obligations under the FCA's (2022a) Consumer Duty.

Specifically, 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 require firms to act to deliver good outcomes for retail customers. Among other rules, it requires firms to act in good faith towards retail customers, avoid causing foreseeable harm to retail customers, and to enable and support retail customers to pursue their financial objectives. The Consumer Duty also calls for firms to ensure retail customers do not face sludge ("unreasonable barriers") during the lifecycle of a product (FCA, 2022a, 2022b). Of particular relevance to this work are the requirements under the Duty's consumer understanding outcome and, in relation to the requirement to act in good faith, the expectation that firms avoid designing features which exploit the behavioural biases of consumers. (FCA, 2022b).

With these concerns in mind, the FCA has highlighted the need for trading app firms to review their design features to ensure they do not contribute to poor consumer outcomes, and to monitor this on an ongoing basis (FCA 2022c, 2024a).

The contributions of this paper

This paper builds on and complements our previous survey and experimental results (Gathergood et al., 2024; Hayes et al., 2022). Noting the external validity concerns with such studies (Nieboer, 2020), the administrative dataset that we have analysed in this paper places us uniquely to comment authoritatively on measures of app engagement, trading behaviour and trading outcomes. Using administrative data (as opposed to self-reported data) can contribute to a more reliable basis to make conclusions about the extent to which trading app consumers are, for example, making losses or are in financial distress outside of their use of the apps. To our knowledge, this is the first publicly available analysis comparing UK investor behaviour across multiple trading apps and our hope is that it will be instructive to financial regulators and to firms that seek to meet their existing obligations under the Consumer Duty.

3 Research design

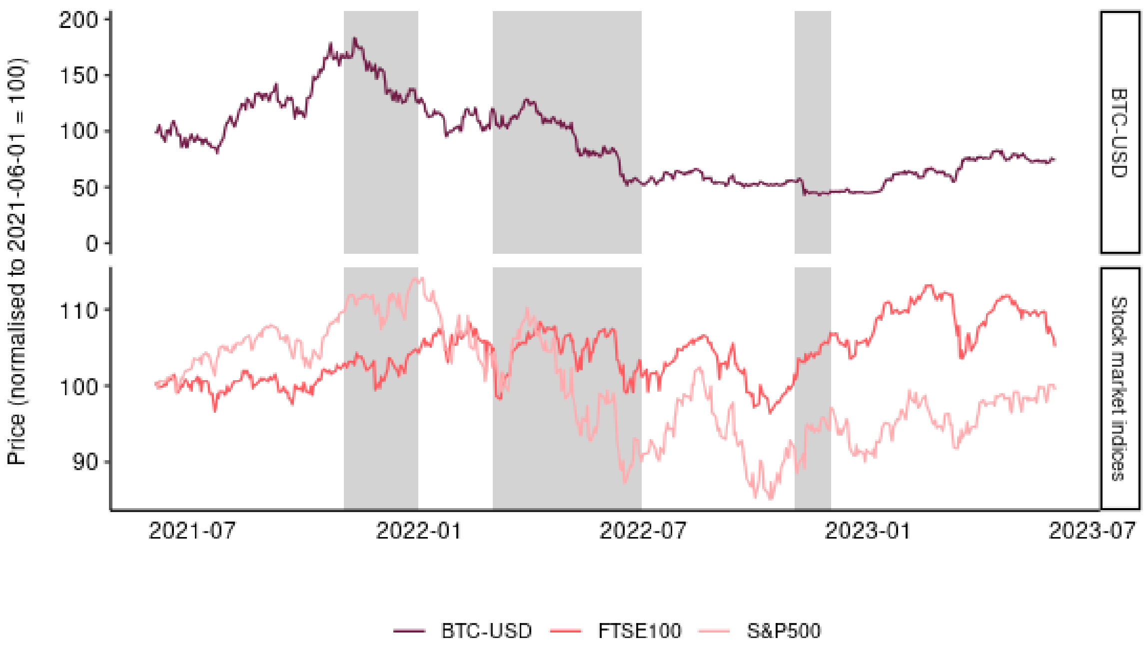
Data

Trading app (TA) data

We worked in collaboration with several of the trading apps and platforms with the largest UK customer bases to collect data from a large representative random sample of their UK customers. The data collected from firms related to five broad areas: customer demographic data, trade data, portfolio holdings data, app usage data and daily returns data. The dataset was designed to ensure we could analyse a range of consumer trading behaviours and outcomes.

In most instances, the data weas collected for three separate time-periods (1 November 2021 – 31 December 2021; 1 March 2022 – 30 June 2022; 1 November 2022 – 30 November 2022), resulting in 7 months of trading behaviour and outcomes within a period of 13 months. Three timepoints were chosen to ensure coverage when the market was trending slightly upwards, trending downwards and additionally the most up-to-date time period available at time of data collection. Further information about the TA data is given in Table 1 in Annex 1. Broader context of financial market trends around the time of our study is shown in Figure 2. The periods for which we have data are shaded in grey. The price of each on 1 June 2021 is indexed to 100 to show relative price changes.

Figure 2. Price movements of FTSE100, S&P500, and Bitcoin



Credit reference agency (CRA) data

We linked the TA data to consumer-level data we hold from one of the UK's top three credit reference agencies (CRA) using unique identifiers present in both datasets. The CRA data contains information on a consumer's credit position, including current account turnover and balances on credit products.

We worked with net income (income after all deductions such as taxes have been subtracted) because it is more relevant than gross income when we are considering the extent to which an investment loss impacts an investor. Our estimate for net income, following Belgibayeva et al. (2020) and Guttman-Kenney and Hunt (2017), was calculated using median monthly 'current account turnover' (a measure of funds flowing into and out of personal current accounts) from the CRA data.

In addition, we used the CRA to establish whether consumers were in financial distress. Following Belgibayeva et al. (2020), which in turn was based on a measure of serious delinquency used by the US Federal Reserve Board (2007), an individual was taken to be in financial distress if at least one of the following held at the time:

- They had reached arrears of 90 days (or a default) on any credit product or bill.
- They had a county court judgement (CCJ) issued against them.
- They had been declared bankrupt in the last 18 months.
- One of their credit accounts had been passed to a debt collector in the past 18 months.

We linked the TA and CRA data so that we could understand a consumer's wider financial position. For example, this enabled us to compare the size of their portfolio and any returns to their current income, and to evaluate the extent to which they were experiencing difficulties with any credit products. We were able to match 63% of the individuals in the TA data to their associated credit profile. The lack of exact match is explained by data quality issues on mutual identification variables as well as the fact that some trading app customers may not have an associated credit record in the CRA dataset.

We compared those in our sample with and without a CRA match in Annex 2. We found that, across key demographic variables and behaviour on the trading apps themselves, investors with and without a CRA match were not substantially different. For our analysis throughout this paper, we only excluded investors without a CRA match when we were specifically analysing an outcome that was dependent on the CRA match, such as income level per DEP group or realised return as a proportion of income.

'Investors with active accounts'

We only included those who had a portfolio exceeding £100 at some stage in our data. This restriction was to exclude accounts which may have been opened and (barring some small initial activity) never invested in, or where the funds had been (either entirely or almost entirely) withdrawn prior to our analysis.

After excluding investors without an active account, we had 176,159 investors within our sample. 106,961 of these had a matching credit file. Investors with active accounts were on average 6 years older, 6 percentage points more likely to be male, and had a median net income around £10k higher. A similar proportion of the active and inactive groups could be linked to the CRA data (61% and 62% respectively). The group with inactive accounts was substantially more likely to be in financial distress (18.2% compared to 3.8%). This could reflect investors in distress signing up for the apps but opting not to invest, once considering their options. Alternatively, it could reflect investors withdrawing their money from the app upon becoming distressed.

Approach

Our approach closely followed Hayes et al. (2022). Namely, we reviewed several of the most popular trading apps in the UK to assess the extent to which they featured DEPs on their platform. Examples of these features include trader leaderboards, notifications, and default amounts for investing and leveraging.

From this assessment, we defined three groups: one group of apps with one or fewer DEPs, one group with a medium number (between two and four) and one group with numerous DEPs (five or more). We refer to these groups as low, medium, and high DEP groups, respectively. Our analytical strategy in this paper involved comparing trading behaviour and outcomes across these three groups in an effort to assess the effect of DEPs.

An important caveat is that the apps (and by extension the groups of apps) in this study do not differ only in the number of DEPs they feature. They also differ, for example, in terms of the product offering (which categories of instruments one can trade in). Most notably, CFDs and cryptoassets were offered by some of the high DEP apps within our sample, but none of the low or medium DEP apps. To tease apart the effect of DEPs compared to CFD trading in general, we make additional comparisons between users of high DEP apps that did and did not use CFDs. Due to limitations in the data, we were unable to compare the behaviour of cryptoasset traders in the same level of detail. Moreover, and perhaps by extension, the types of consumers to sign up for and engage with the different apps may differ in meaningful ways.

Due to such differences, which could influence trading behaviour and outcomes, we cannot conclude directly on the *causal* input of DEP preponderance on trading apps in this work. To combat this, we had requested the results of the firm's own testing of the causal impact of DEPs on our outcomes of interest, but none of the firms had conducted such testing as of the end of December 2022.

Nonetheless, the grouping of firms in terms of preponderance of DEPs helps us understand correlations, if any, between DEPs and trading behaviour and outcomes.

Where comparing across groups of firms is not possible, for example because some firms or groups of firms do not offer cryptoassets or contract for differences (CFD) products, we deviated from our analytical approach and instead conducted our analysis only on the sample of investors that have access to those products.

Level of analysis

We conducted most of our analysis at the level of the DEP group i.e., we compare trading behaviour and outcomes across the low DEP, medium DEP, and high DEP groups. In instances where consumers had accounts with multiple firms – whether these firms are in the same DEP group or different DEP groups - we included these accounts as separate observations in our analysis. So, for example, an individual with an account at two firms in the low DEP group and one account at a firm in the high DEP group would appear three times in our analysis - with different observations for each of their separate firm accounts, respectively.

Hypotheses

Our primary hypothesis is that the more DEPs there are on the apps, the worse the consumer outcomes. Reflecting this, we expected to see:

(i) a negative association between DEPs and returns

The first mechanism for this that we propose is that DEPs could be influencing consumers to display 'potentially problematic engagement' (PPE) behaviours, which in turn result in poorer returns. As a result, we expected to see:

(ii) a positive association between DEPs and PPE
(iii) a negative association between PPE and returns

The second mechanism that we propose is that DEPs could be influencing consumers to trade in certain high-risk investments (HRIs) namely CFDs and cryptoassets, which in turn results in poorer returns. This could be particularly detrimental if those HRIs lie outside their risk appetite, leading to unexpectedly sharp losses. Due to data availability, we cannot assess whether investment decisions are in line with risk preferences, and we also cannot directly evaluate whether DEPs are encouraging the use of HRIs. We can however provide evidence of the relationship between such products and returns over the course of our study. Hence, we expected to see:

(iv) a negative association between use of CFDs/cryptoassets and returns

We define 'potentially problematic engagement' (PPE) as elevated, erratic, or concerning trading behaviour on trading apps. To measure this, we constructed an index of eight metrics, inspired by the problem gambling literature (e.g., Catania & Griffiths, 2022). We outline exactly what is included in this index in Table 11 in Annex 4. Some of the measures include day trading, a lack of diversification (maintaining a portfolio with only one asset) and investing while being in credit arrears by more than 90 days. In collaboration with an academic expert in the field of gambling and problem gambling (Mark D. Griffiths) we set thresholds for each measure, and investors meeting or exceeding those thresholds are flagged as exhibiting potentially problematic engagement. We expected that investors that displayed potentially problematic engagement would achieve worse returns.

Outcomes

We used three measures of investment returns:

1. **Realised returns:** returns that are actualised or crystalised once an investment has been sold or a position has been exited, net of all transaction charges. We scaled these returns by net income, as estimated from the CRA.
2. **Unrealised returns:** returns that accrue on investments that have not yet been sold or more generally on positions that remain open. Again, we scaled by net income.
3. **Large losses:** a binary indicator as to whether a consumer has realised losses equivalent to more than 2% of their pro rata net income. Unrealised losses were not considered here due to the variability of time horizons over which they accrued.

The two possible approaches to scaling returns in line with their likely impact on an investor's financial wellbeing are to scale according to income or wealth (proxied using portfolio value). A drawback of the latter is that portfolio value cannot capture wealth not held on the specific platforms from which we have data, such as property or other accounts, though it would offer a comparable measure of performance across platforms.

Unfortunately, due to time gaps in our data we did not have the requisite information to implement a returns measure scaled by portfolio value such as the time-weighted rate of return, but we were able to scale by estimated net income using data from the CRA.

As covered later in the results section, the median portfolio value was around ten to fifteen times larger on low DEP accounts than medium or high DEP accounts, whereas median net income was only around 1.25 times larger. Consequently, measures of returns (either losses or gains) look relatively larger for low DEP groups when comparing to income rather than portfolio value.

We are particularly interested in occasions where 'large losses' are realised. Unrealised losses were not considered here due to the variability of time horizons over which they accrued. To put the 2% threshold into context, the median net income in our sample was £36,477 (equivalent to a pre-tax salary of approximately £48,000 in 2021/2022). A 2% loss at this net income would equate to losing £426 across our 7-month period. As a robustness check, we also checked our results at the 5% and 10% levels, equivalent of the average person in our sample losing £1,064 and £2,128 over our timeframe, which led to similar conclusions.

Models

First, we estimated the association between our eight individual measures of potentially problematic engagement (see Table 11 in Annex 4) and the DEP group (low, medium, high). We did the same for the potentially problematic engagement index score (0, 1-2, 3-4, 5+) and the DEP group. For the first regression, because the outcome was binary (either the threshold was met for a PPE behaviour or it was not) we used logistic regression as indicated in equation (1a) below. For the second regression, where the outcome measure was PPE score, we used linear regression (ordinary least squares) as outlined in equation (1b), below.

In these regressions (1a & 1b), and all regressions below (2a – 2d), we controlled for (took into account) age (18-24, 25-34, 35-44, 45-54, 55-64, 65+), gender (male, female), and length of tenure with the trading app in question (0-1 year, 1-2 years, 2-3 years, 3+ years). In all of our regressions, we also checked whether our results were robust to the inclusion of dummy variables ($\beta_5 CFD$ and $\beta_6 Crypto$) that indicated whether an investor had traded or held CFD or cryptoassets products at any point in our study. This is to account for the possibility that potentially problematic engagement and poorer returns are driven, in fact, by CFD and/or cryptoassets use rather than the preponderance of DEPs on an app.

$$(1a)\ logit(PPE_{measure}) = \beta_0 + \beta_1 DEPgroup + \beta_2 age + \beta_3 gender + \beta_4 tenure + e$$

$$(1b)\ PPE_{score} = \beta_0 + \beta_1 DEPgroup + \beta_2 age + \beta_3 gender + \beta_4 tenure + e$$

Next, we estimated the relationship between our outcome measures (unrealised returns, realised returns, and large losses) and a set of explanatory variables. For completeness, we included an additional regression for "total" return, which amounts to the sum of unrealised and realised returns. In separate regressions, we took the primary explanatory variable (x_1) to be (i) DEP group (low, medium, high), (ii) potentially problematic engagement index score (0, 1-2, 3-4, 5+), and (iii) the individual measures of potentially problematic engagement index, such that there were twelve regressions in total.

For the regressions where the outcome variable was continuous (unrealised, realised, or total returns), we used linear regression as set out in equations (2a), (2b), and (2c) below, where x_1 takes the value of one of our sets of explanatory variables, (i) – (iii). For the regression where large loss was the outcome, because this is a binary outcome, we used logistic regression, as set out in equation (2d) below, where again x_1 represents our primary explanatory variables, (i) – (iii).

$$(2a)\ \frac{Unrealised\ returns}{Pro\ rata\ net\ income} = \beta_0 + \beta_1 x_1 + \beta_2 age + \beta_3 gender + \beta_4 tenure\ + e$$

$$(2b)\ \frac{Realised\ returns}{Pro\ rata\ net\ income} = \beta_0 + \beta_1 x_1 + \beta_2 age + \beta_3 gender + \beta_4 tenure + e$$

$$(2c)\ \frac{Total\ returns}{Pro\ rata\ net\ income} = \beta_0 + \beta_1 x_1 + \beta_2 age + \beta_3 gender + \beta_4 tenure + e$$

$$(2d)\ logit(Large\ loss) = \beta_0 + \beta_1 x_1 + \beta_2 age + \beta_3 gender + \beta_4 tenure + e$$

4 Results

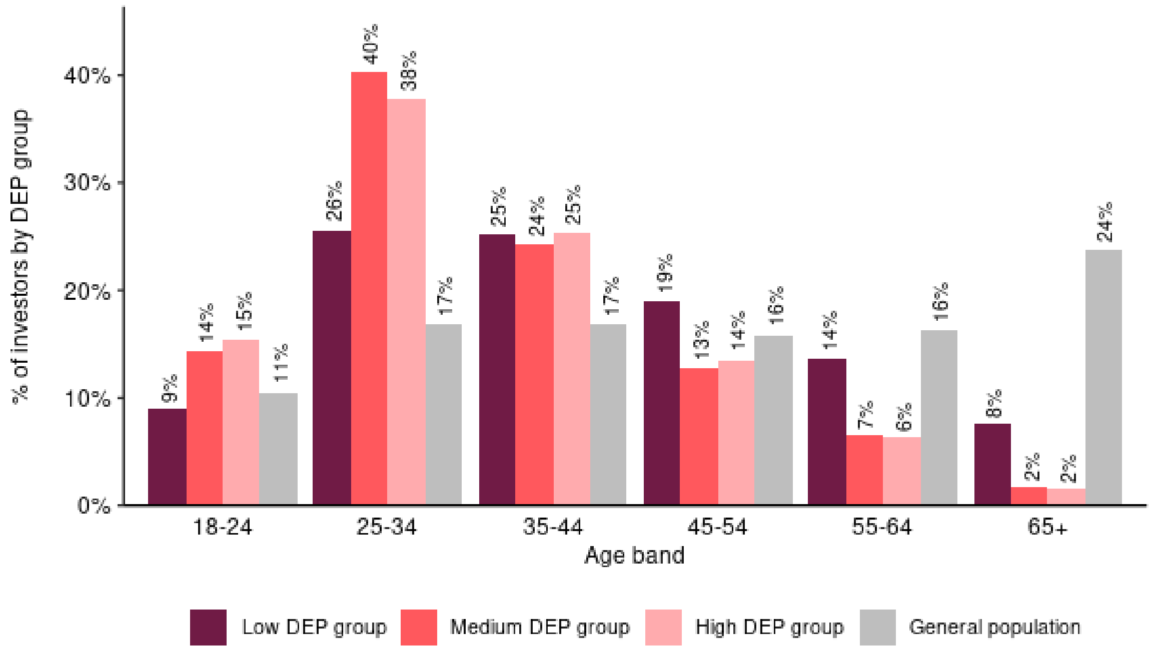
Demographics

The average user of high DEP apps was 6 years younger than the average user of low DEP apps, and 15 years younger than the UK adult population median.

The median ages of investors on low, medium, and high DEPs were 40, 33, and 34 respectively, compared to a median age of 48 in the UK adult population (ONS, 2024a). As can be seen in Figure 3, 28% of UK adults were aged 18-34. However, more than half of medium (54%) and high (53%) DEP app users were between the ages of 18-34, with fewer than 10% over the age of 55. Within the high DEP group, users who held or traded contracts for differences (CFDs) were on average 2 years older than those who have not.

The difference in user ages between apps, may - in part - explain why accounts with low DEPs had on average been open longer, with 53% of accounts open for more than 3 years compared to only 8% of medium and 12% of high DEP accounts.

Figure 3. Age of investors



Nearly 4 in every 5 investors (79%) on trading apps were male. This proportion was highest for high DEP apps (83%), compared to low (76%) and medium (77%) DEP apps respectively.

Consistent with previous research that found a substantial gender gap in investment (FCA, 2023a), we found that men were much more likely to invest than women via trading apps. CFD trading was even more male-dominated – 86% of those who held or traded CFDs were male. Moreover, we found that the median portfolios held by men (£2,572) were 18% larger than those held by women (£2,185).

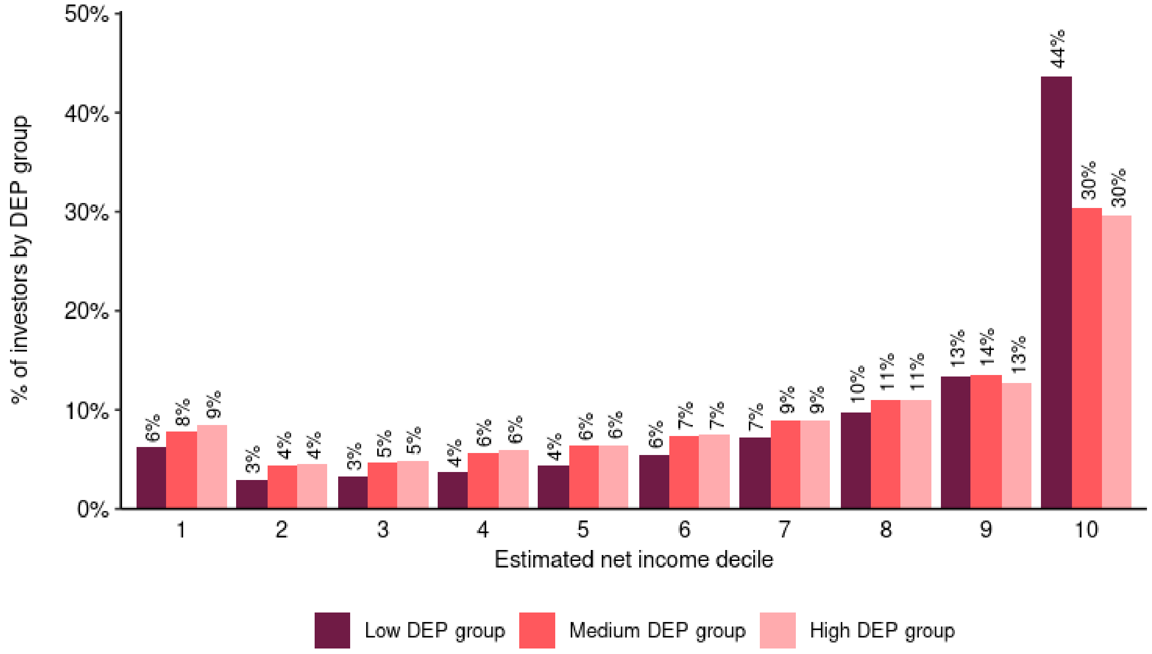
Here, as in the rest of our analysis, we used a classification algorithm to predict gender in the (37% of) cases where gender data was missing from our sample - further details are provided in Annex 2. Reassuringly, at least statistically, the alternative approach of excluding missing gender data similarly found that the proportion of our sample that was male remained at 79%.

The median net income for trading app users was over £12,500 higher than the median UK taxpayer, and was around £10,000 higher for those on the low DEP apps than the high DEP apps.

The median net income - income after all deductions such as taxes - of our sample was £36,477, compared to a UK taxpayer median of £23,800 (ONS 2024b, 2024c). The median was £33,654 for high DEP apps (similar for both CFD and non-CFD investors) and £34,596 for medium DEP apps, compared to £43,839 for those on the low DEP apps.

As shown in Figure 4, where each decile is defined to represent 10% of UK taxpayers, 44% of low DEP users were in the top 10% of UK taxpayers, compared to 30% of medium and high DEP apps.

Figure 4. Annual net income of investors

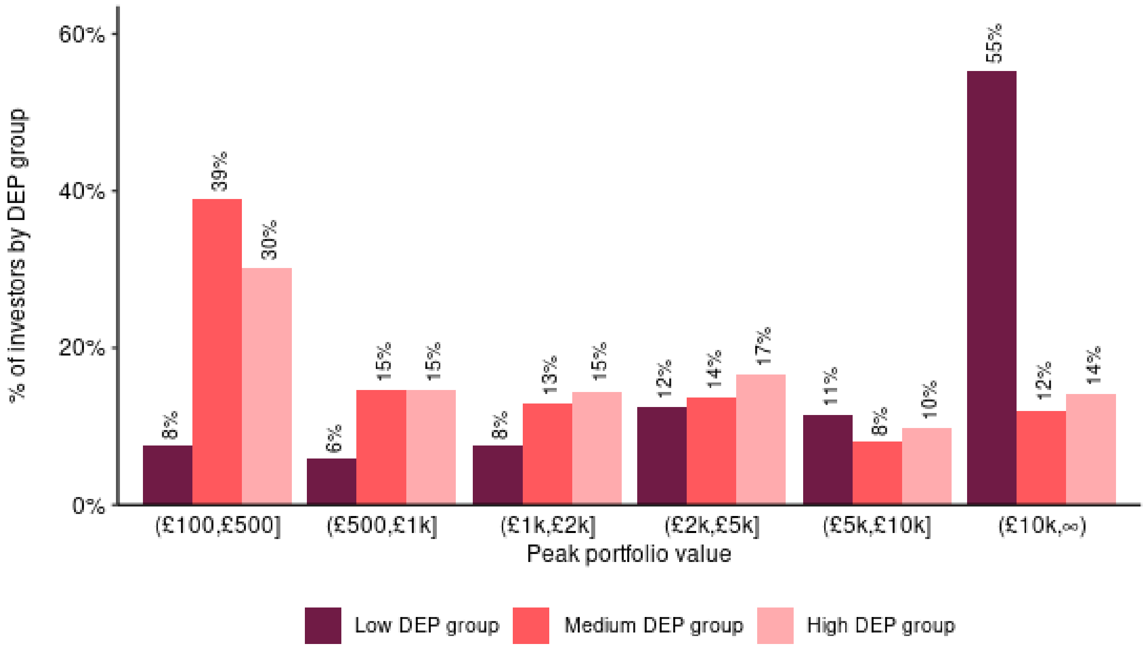


Over half (55%) of portfolios on the low DEP apps had values of over £10,000, compared to only 12% and 14% respectively of portfolios on the medium and high DEP apps.

The median (mean in brackets) peak portfolio size of our sample, excluding cash, was £2,382 (£29,729). Customers with accounts on high DEP apps had a peak portfolio size of £1,255 (£7,266) and those on medium DEP apps had a peak portfolio size of £852 (£5,488). Customers on the low DEP apps had a median peak portfolio size around of £13,348 (£72,431), more than ten times higher than those on high DEP apps. Among high DEP investors, those that used CFDs had portfolios on average twice as large as their peers that did not use CFDs.

Nearly half of portfolios on high (45%) and medium DEP (53%) apps were valued at less than £1000, compared to only 13% of those on the low DEP apps (Figure 5).

Figure 5. Highest observed value of portfolio



We had requested demographic data on a wider range of variables including ethnicity, education level, employment status, risk preference, and vulnerability. However, the firms in the sample collected demographic data on a relatively small range of variables. In addition, demographic data collected was not always recorded in a consistent way, making aggregation across firms difficult.

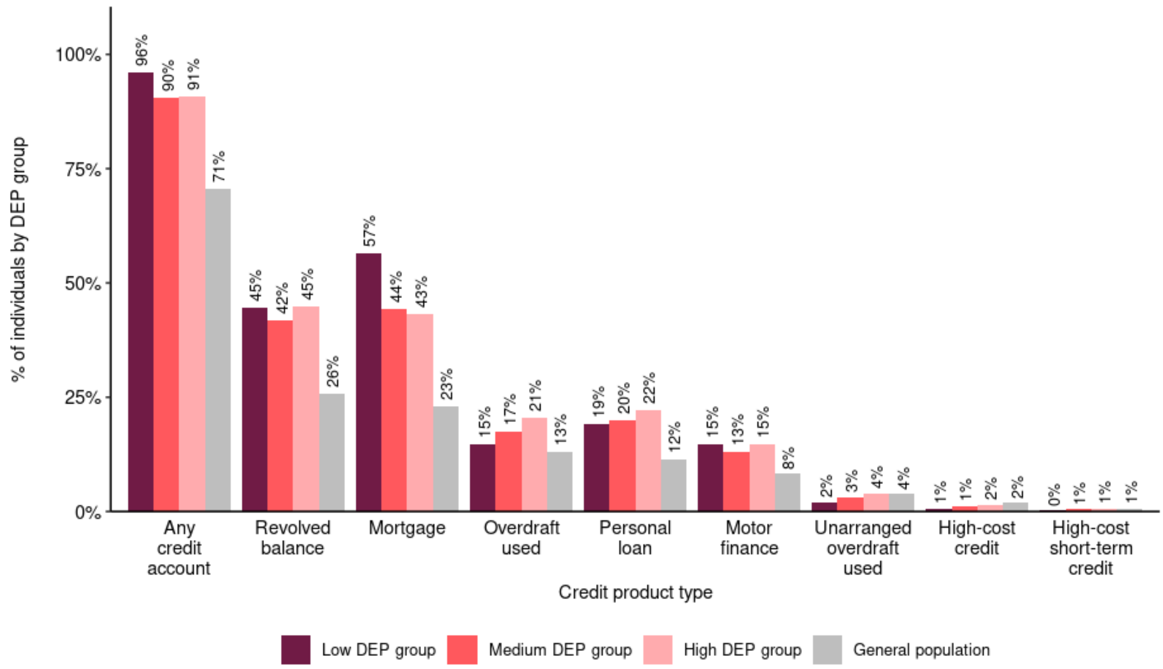
Credit position

Trading app users – regardless of DEP group - were more likely than the general population to hold most types of credit product.

As shown in Figure 6, users of trading apps across all DEP groups were more likely to hold a range of credit products (any credit product, mortgages, personal loans, motor finance, revolving credit card balances, and overdrafts) when compared to the general population (defined as all those with a credit file from the CRA). The exceptions to this were unarranged overdrafts, high-cost credit, and high-cost short term credit, where rates of use were similar in both groups.

Users of the low DEP apps were significantly more likely (57%) to be mortgage holders than users of the medium (44%) or high DEP (43%) apps, though around half of the difference can be accounted for by differing age and income profiles. This corroborates our findings on net income and portfolio wealth - that those investing via low DEP apps are generally wealthier. Among users of high DEP apps, users of CFDs were slightly more likely than non-CFD users to hold each of these types of credit product, except mortgages.

Figure 6. Credit products held



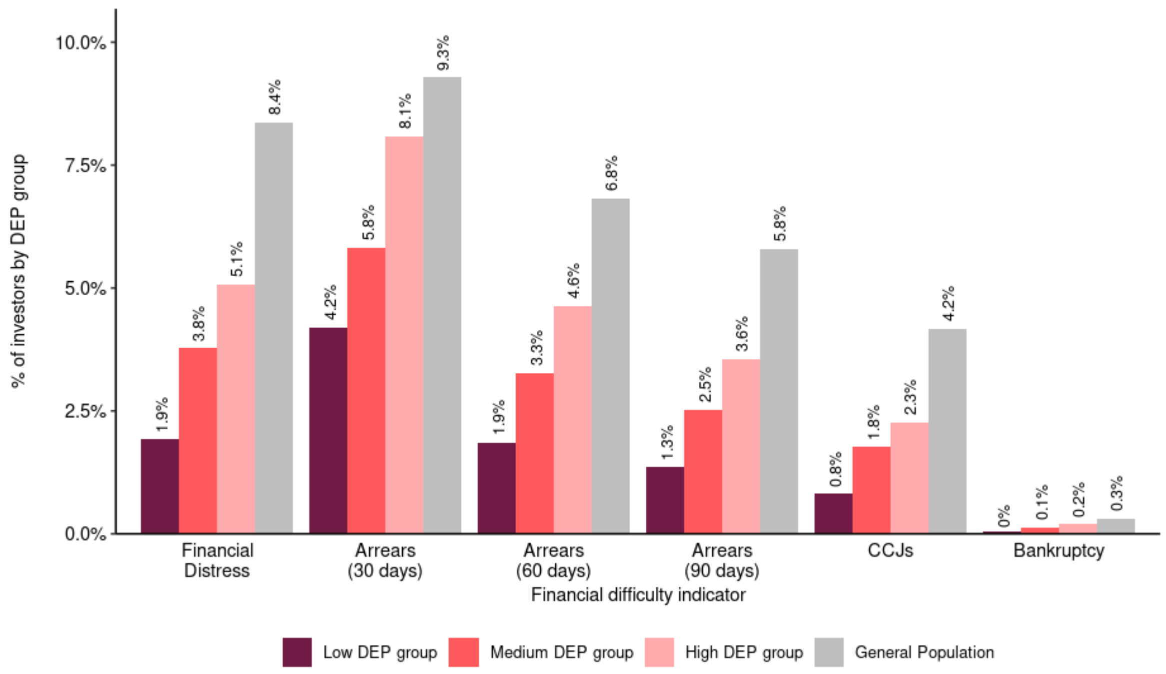
Financial distress is less prevalent among trading app users (3.8%) than the UK general population (8.4%). However, the high DEP group had a rate of users in distress (5.1%) that was over twice as high as the low DEP group (1.9%). This rate increased further to 7.3% for CFD users.

In most cases, it is advisable for an investor who is in financial distress – most commonly because they are in 90 days of arrears or have an active county court judgement (CCJ) against them - to close some positions and use the funds to pay down outstanding debts. This is because the interest rate or financial penalty on debt in arrears is likely to be significantly higher than the expected return on an equivalently sized investment (FCA, 2024b).

Opting not to close positions to pay off debt could indicate a lack of an awareness of either the outstanding debt or indeed the trading app account with funds to pay off that debt. However, it could also indicate other factors including a consumer's decision to attempt to invest out of their acute money problems – which may be based on an unrealistic expectation of investment return - or a reluctance to sell assets while investments are down on their original purchase value (Shefrin & Statman 1985). Rates of financial distress, and the constituent indicators of financial difficulty, are shown in Figure 7.

Even constraining our analysis to portfolios worth at least £5k at the end of our study period (where it is highly likely that liquidating the account in part or in full would help clear debts) and excluding funds held in self-invested personal pensions (SIPPs) by people under the age of 55 (as these cannot easily be withdrawn), we found that 1.4% of people on trading apps were in financial distress. We saw this most often among users of high DEP apps (3.2%), compared to medium (1.1%) or low (0.8%) DEP apps. This equates to 0.29%, 0.15%, and 0.33% of the overall user base of the high, medium, and low DEP apps respectively, reflecting the larger share of low DEP app users with substantial portfolios.

Figure 7. Indicators of financial difficulty



App engagement

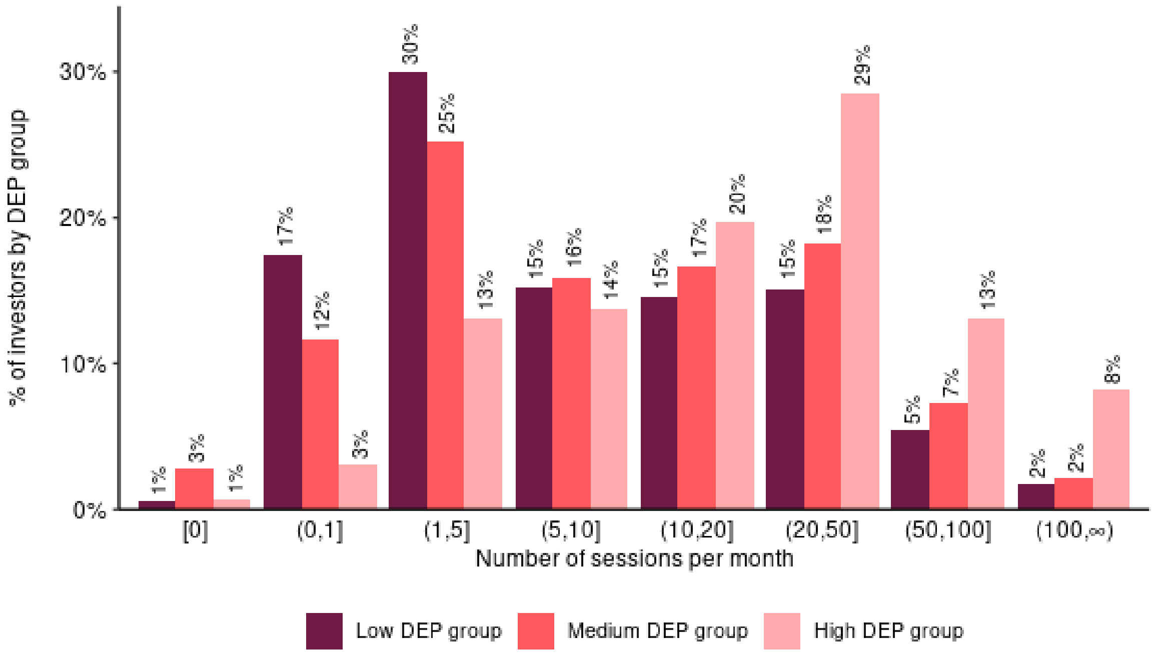
Some firms could not provide reliable data on the following app engagement measures: frequency of sessions, number of 'active' days, time spent on platform, and night sessions. These firms were excluded from the relevant analysis below.

Users of high DEP apps logged in more frequently, with 21% of users averaging more than 50 sessions per month, compared to 10% of medium and 7% of low DEP apps users.

The median (mean) number of sessions in the total sample was 7 (18) per month. This varied from 6 (15) in the low DEP apps to 8 (18) in the medium DEP apps and 20 (36) in the high DEP apps (Figure 8).

The median trading apps user – regardless of DEP group – was active on the app (i.e., accesses the platform at least once) between one and two days a week. However, users of high DEP apps were more likely to be active six or more days per week. Specifically, 4.6% (4.2% excluding CFD users) of high DEP app users were active six days a week on average, compared to only 1.9% of medium and 1.4% of low DEP users. The share of CFD users active six or more days per week on average was 8.5%.

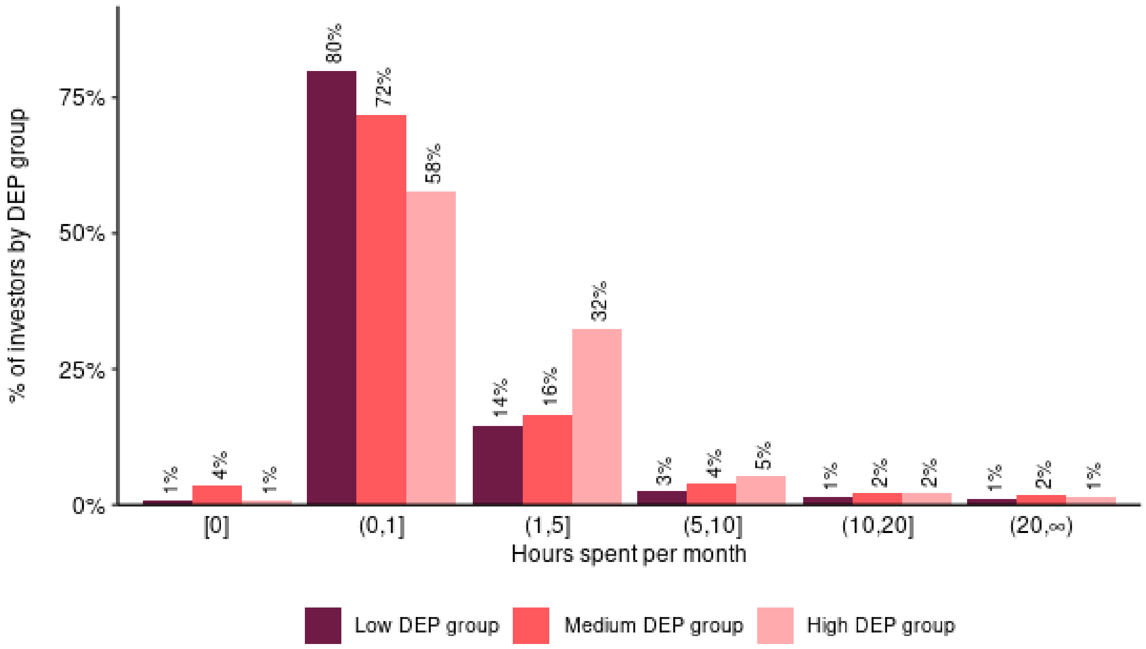
Figure 8. Number of app sessions per month



The median user of high DEP apps spent over three times longer on the apps per month (44 minutes) than median users of the medium (13 minutes) or low (12 minutes) DEP apps.

The median (mean) time spent on the platform in the total sample was 14 minutes (1.5 hours) per month, with an average session lasting 24 seconds (5.2 minutes). 81% of investors on low DEP apps, around four in five, spent an hour or less per month on the app, compared to 75% of medium DEP users and 59% of high DEP users. The mean durations were substantially higher than the medians for all app groups, driven by users at the extreme - 3.1% of users were active for more than 20 hours per month (Figure 9).

Figure 9. Number of hours spent on the app per month

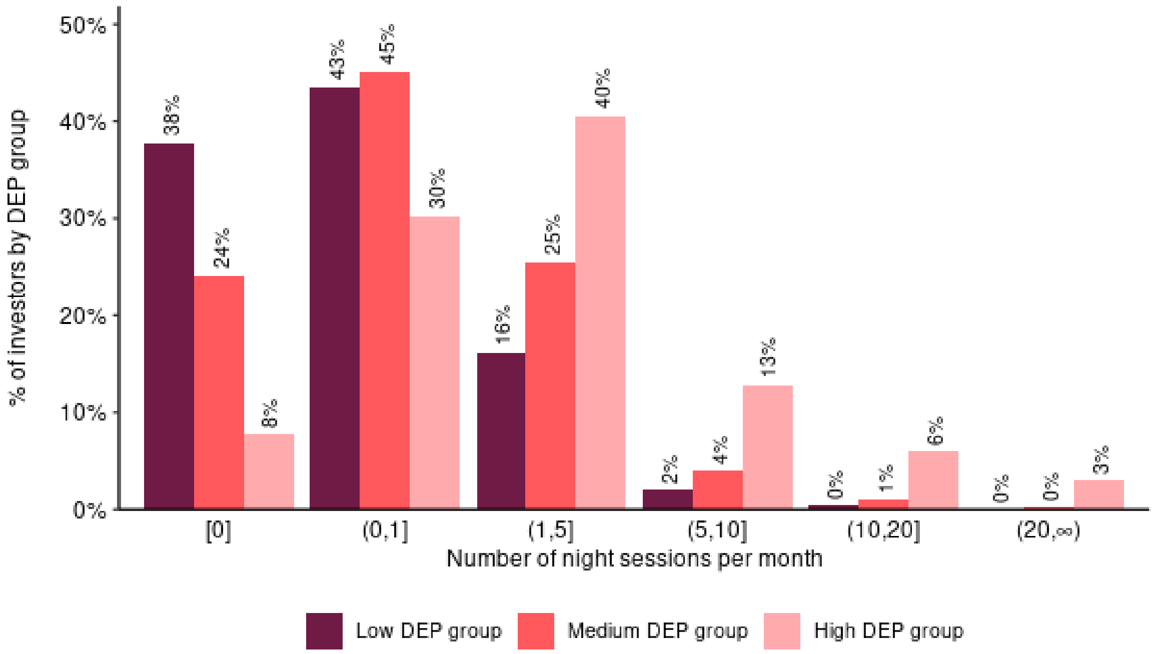


Users of high DEP apps logged in at night (between 11pm and 6am) four times as often as any other app group. They were also more likely to trade at night.

The median (mean) number of night sessions per investor in the total sample was 0.3 (1.2) per month. This ranged from 0.1 (0.8) in the low DEP apps to 0.4 (1.3) in the medium DEP apps and 1.7 (3.9) in the high DEP apps (Figure 10). Moreover, a higher proportion (17%) of high DEP investors made at least one trade between 11pm and 6am, as compared to 13% of medium and 5.1% of low DEP investors.

Night sessions and trades may simply be indicative of the different demographics of the respective user bases of the apps – with younger people more likely to stay up later, perhaps because they are engaged in shift work. Likewise, the markets for different asset classes have different opening hours – equity markets are only open during local business hours, while cryptoassets and some CFDs can be traded 24/7. However, night sessions could also suggest a preoccupation with investment, and on gambling apps it has been associated with problem gambling behaviour (GambleAware, 2017).

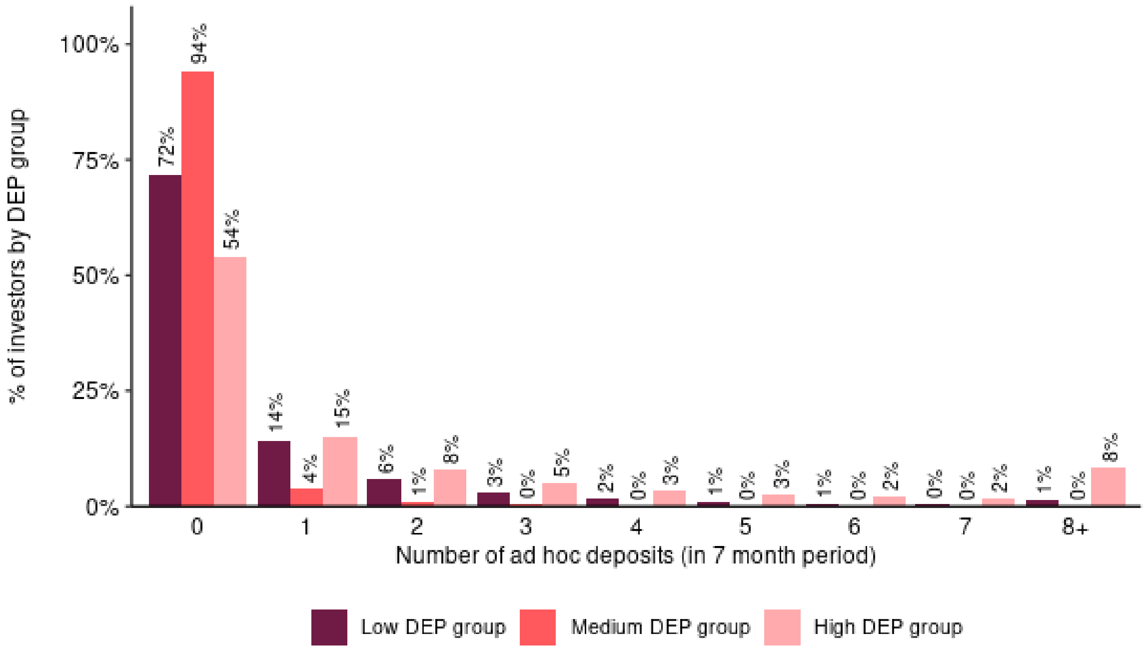
Figure 10. Number of app sessions between 11pm-6am per month



High DEP app users were more likely to make 'ad hoc' deposits. They were also more likely to make a deposit and withdrawal in the same day.

Our deposits data only included 'ad hoc' deposits - deposits initiated manually in the app on a one-off basis. It is likely that many investors were using standard orders to make regular payments into their accounts, but we could not observe these. Nearly two thirds (65%) of investors made no ad hoc deposits during our seven-month study period (Figure 11), and over three quarters (78%) made no withdrawals. High DEP app users were most likely to make ad hoc deposits, with 1.2% of high DEP app users (0.8% excluding CFD users) averaging one or more ad hoc deposit per week, compared to around 0.05% of low DEP app and medium DEP app users. Among the high DEP group, CFD users were more than three times as likely to have deposited at this rate. Since CFDs are often traded on leverage, users are sometimes required to add further collateral ('variation margin') to keep a position open if it moves against them. This is likely why we see CFD users making more ad hoc deposits.

Figure 11. Number of ad hoc deposits in full 7-month period



In addition, high DEP app users were more likely to have had at least one day containing both a deposit and a withdrawal (3.9%, or 3.1% excluding CFD users) than medium (0.2%) and low (0.3%) DEP app users. This share was 6.9% for CFD users.

Drawing a parallel to the gambling literature, frequent manual depositing may suggest impulsivity rather than careful planning and in the gambling literature has been associated with problem gambling and self-exclusion (Auer and Griffiths, 2023; Hopfgartner et al., 2022; Luquiens et al., 2016). Depositing and withdrawing on the same day may be indicative of impulsive behaviour on the app, as we explore in Annex 4.

A substantial minority (10%) of trading app users were active on more than one app (multi-homers).

Accounts of users that were multi-homing comprised 16% of our sample, with 12% of the accounts on low, 20% of the accounts on medium and 18% of the accounts on high DEP apps belonging to users active on multiple platforms. CFD users were about as likely to multi-home as their non-CFD user peers on the high DEP apps.

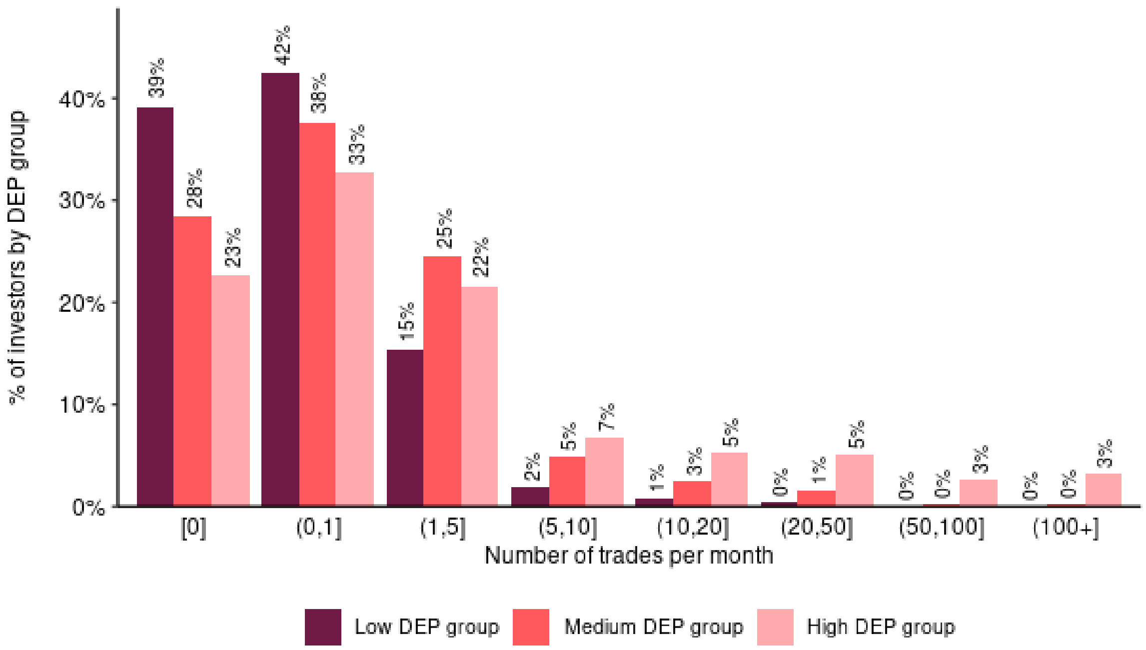
Trading behaviour

High DEP investors traded more frequently, with 16% averaging 10 or more trades a month (or 7.4% if CFD traders are excluded), compared to only 4.6% of medium and 1.2% of low DEP investors.

The median (mean) number of monthly trades made in our sample was 0.4 (8.4). Customers with accounts on high DEP apps traded the most, making 0.7 (15) monthly trades on average, compared to 0.4 (2.6) and 0.1 (1) for the medium and low DEP groups respectively. This was substantially higher for CFD users, who averaged 8.3 (54.3) trades per month across the period. This is expected, as CFDs are a short-term speculative product not designed to be held for extended periods of time.

In total, 39% of low DEP investors did not trade at all throughout the 7-month period, compared to 28% of medium and 23% of high DEP investors (Figure 12).

Figure 12. Number of trades per month



Nearly a quarter (24%) of high DEP app users engaged in day trading at least once (or 14% if CFD traders are excluded), compared to only 8.7% of medium and 3.2% of low DEP users. This rose to nearly two thirds (65%) among CFD traders.

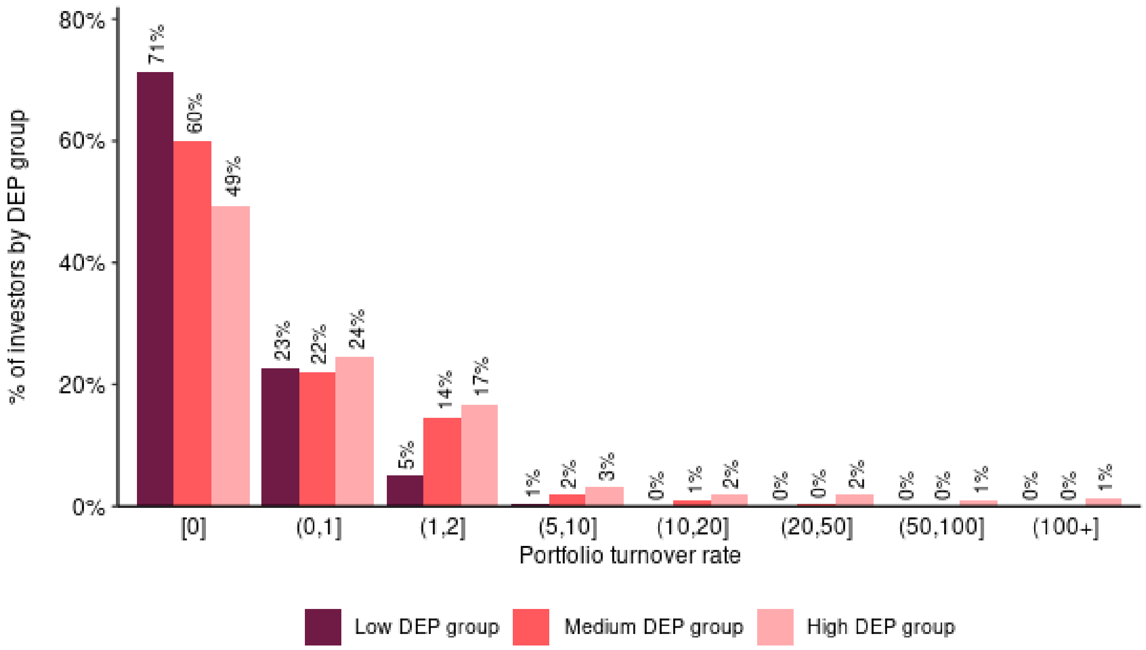
Day trading is defined as both opening and closing a given position in a single day. As a result of price volatility and transaction costs, previous research has found that only around 5% of day traders make a profit (Barber et al., 2014).

Another measure of trading frequency is 'portfolio turnover,' which captures how often funds are withdrawn from their existing positions and reinvested. A user that starts with £100 of *asset A*, sells all of this, and buys £100 of *asset B* will have a 'turnover' of 1. If the user then sold all of their *asset B* holdings and bought instead £100 of *asset C*, their 'turnover' would be 2. We describe how we estimate portfolio turnover in Annex 4.

The median (mean) level of turnover in the sample was 0.0 (3.7), which is to say that the median user had not liquidated and reinvested any assets at all. However, driven by users at the extreme – in particular on the high DEP apps - the mean portfolio had been liquidated and reinvested 3.7 times over throughout the 7-month period. For example, 26% (10%) of users on high DEP apps had a turnover of more than 1 (more than 5), compared to 18% (3.9%) of users on medium DEP apps and 6.3% (0.9%) of users on low DEP apps (Figure 13). The higher turnover of high DEP investors was largely driven by CFD traders, of whom 67% had a portfolio turnover above 1 and 37% over 5.

All else equal, frequent trading, day trading, and portfolio turnover tend to reduce investment returns owing to any transaction costs and the bid-ask spread (the difference between the price at which investors can sell and buy a given asset) (Barber & Odean, 2000, 2013; Barber et al., 2014).

Figure 13. Portfolio turnover rate in full 7-month period



Holdings on the high DEP apps were less diversified, with 13.1% of portfolios comprising of a single (non-fund) asset, compared to 8.5% in medium DEP apps and 8.7% in low DEP apps.

A lack of diversification has costs for investors, exposing them to more volatile portfolios that need be the case (Bhamra & Uppal, 2019; Calvet et al., 2007). The FCA, via its InvestSmart campaign, encourages investors to hold diversified portfolios, explaining that "spreading your investments across different products and areas makes you less dependent on any one pick to perform for you" (FCA, 2023e). The most extreme form of an undiversified portfolio is one that is invested exclusively in a single (non-fund) asset. In this definition we include single stock/commodity exchange traded products (ETPs), but exclude those that track broader indexes.

Even when we accounted for investors with multiple accounts by factoring in the assets they have across other firms, the equivalent statistics for investors having a single non-fund asset in their portfolio was only about one percentage point smaller for each DEP group (11.8% - high DEP group, 7.4% - medium DEP group, and 7.7% - low DEP group). CFD traders had a slightly lower rate of single-asset portfolios at 9.1%, compared to 12.6% for high DEP investors who had not used CFDs.

In 86% of cases, the single asset being held was an equity, and in 12% of cases it was a cryptoasset. The most popular assets among single (non-fund) portfolios were Tesla (6%), Gamestop (4%), and the cryptoasset XRP (4%).

When we filtered to only look at those investors with larger portfolios (a total closing portfolio size of £5k+) which would be more vulnerable to volatility in absolute terms, the equivalent statistics were not insignificant (3.7% - high DEP group, 2.7% - medium DEP group, and 2.9% - low DEP group).

Cryptoassets and contract for differences (CFDs)

The FCA characterises cryptoassets and CFDs as high-risk, especially when leverage is used to increase exposure (FCA, 2023d). Not all firms across our DEP groups offered contract for differences (CFDs) or cryptoassets to their users. Therefore, we present our analysis on cryptoassets and CFDs aggregated over the full sample of consumers that have access, rather than on the DEP level. There are open questions as to whether - the quantity, intensity or indeed specific - DEPs are associated with different choices regarding cryptoassets and CFDs. However, given our data and the analytical approach of this paper, we cannot explore those questions here.

Among consumers with accounts on apps offering cryptoassets, 67% traded in and/or held cryptoassets.

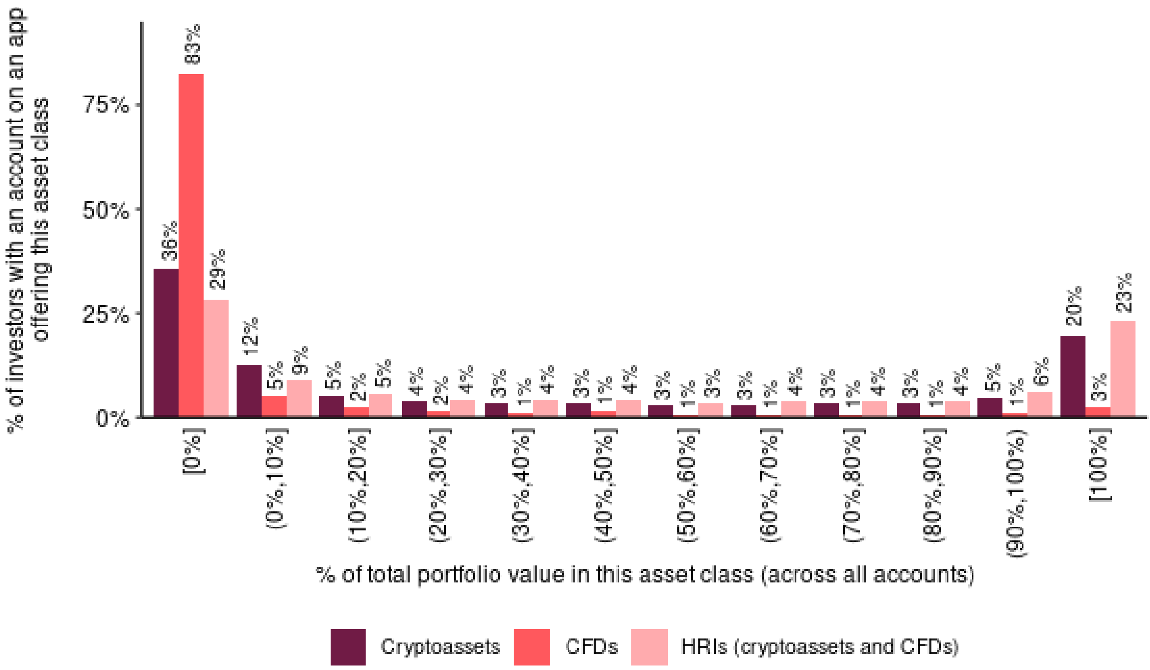
For investors that did invest in cryptoassets, these accounted for on average 63% of their portfolio value on the apps offering the products and 56% of their total portfolio across all their accounts in our sample (Figure 14). The percentage portfolio shares presented here represent the average across six moments in time of the share of portfolio value allocated to the asset class.

The most widely traded cryptoasset (by number of distinct investors) was Bitcoin, which was traded by 42% of cryptoasset investors. This was followed by Cardano (37%) and Ethereum (36%).

Among consumers with an account on a platform offering CFDs, 21% traded in these products. The median leverage on CFD positions opened was 10:1.

For investors that did invest in CFDs, these accounted for on average 36% of the portfolio value on the apps which offering the products and 33% of their total portfolio across all their accounts (Figure 14).

Figure 14. Proportion of total portfolio value held in high-risk products, among investors with an account on an app offering those products

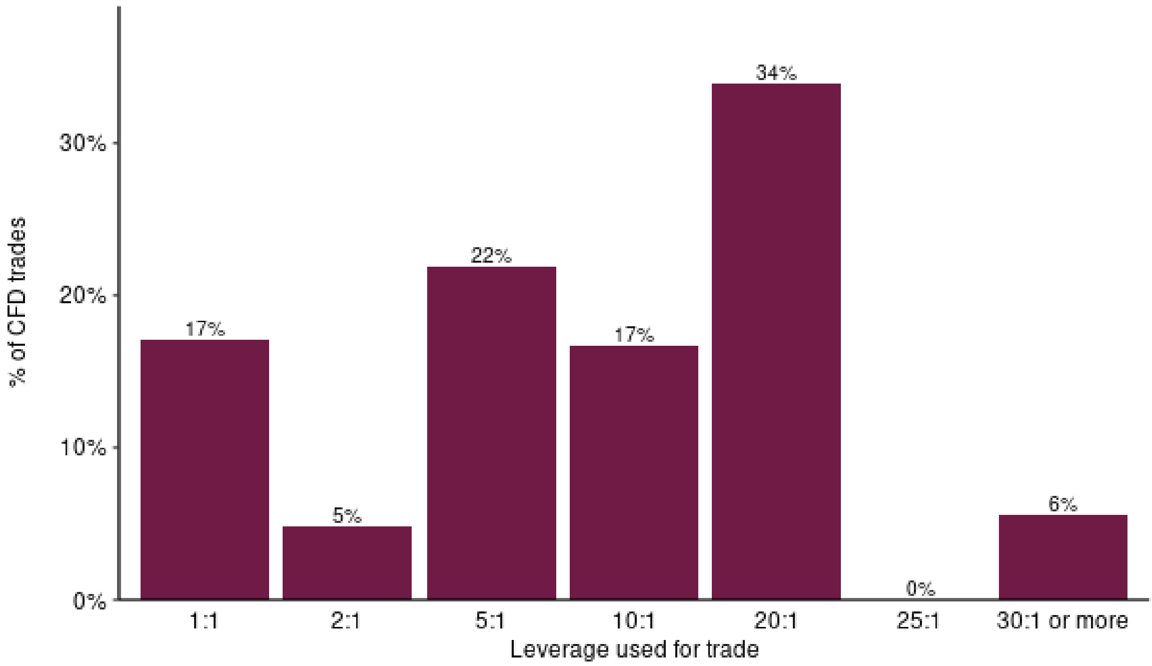


Among consumers who invested in CFD products, the median leverage on each position was 10:1 (Figure 15), meaning that the position was opened with capital worth only 10% of the size of position. In accordance with PS19/18 (FCA, 2019), the maximum permitted leverage for retail trading of CFD products varies according to the underlying asset. These limits vary from 5:1 for equities to 30:1 for major foreign exchange pairs. Two fifths, or 40%, of CFD positions were opened with a leverage of 20:1, meaning that the position was opened with capital worth only 5% of the size of position, and 3.6% of investors who had access to CFD products opened at least one position with that much leverage. At 20:1 leverage, a change in the underlying asset price of only 5% can result in a loss of the entire sum invested.

In total, 38% of investors with an account on a platform offering CFDs or cryptoassets had cumulatively 90% value of their portfolio in CFDs and/or cryptoassets.

Among consumers with accounts on apps offering both cryptoassets and CFDs, on average 68% of their portfolio value on these apps was accounted for by these instruments. Moreover, 62% of their total portfolio across all the accounts in our sample was accounted for by these products (Figure 14).

Figure 15. Rate of leverage used, by number of trades



Potentially problematic engagement

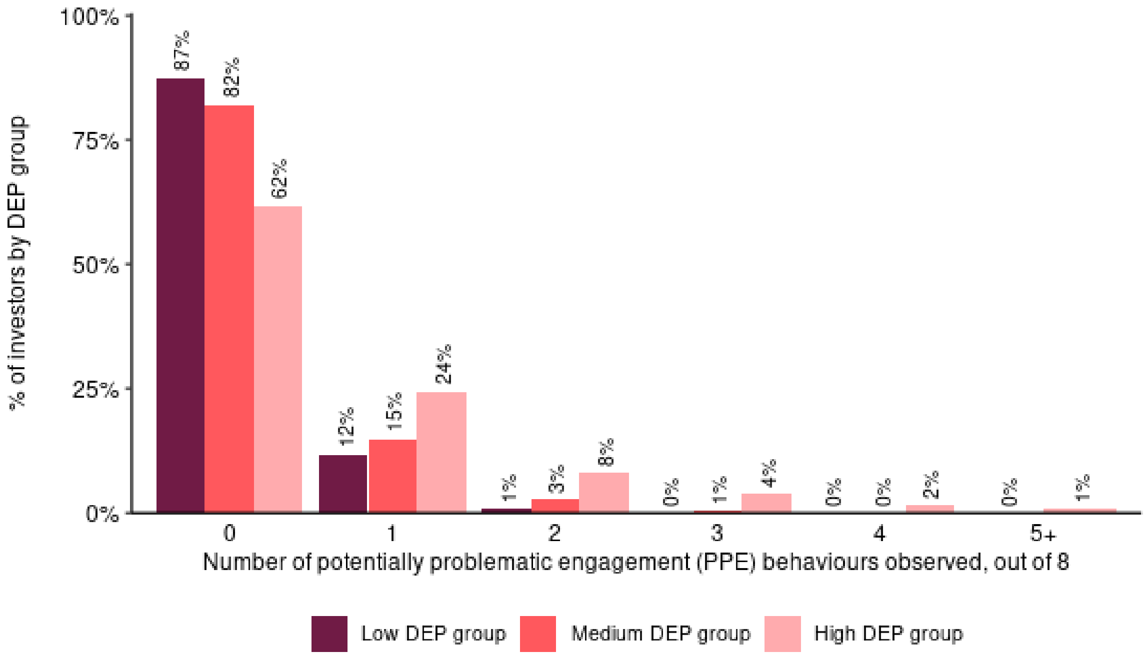
We combined a range of the app engagement and trading behaviour metrics discussed above to establish a potentially problematic engagement (PPE) index (see Annex 4 for details). This PPE index aims to capture elevated, erratic, or concerning trading behaviour and is motivated by the literature on operationalising problem gambling measures (e.g., Catania and Griffiths, 2022). From gambling research, we know that 4.1% of all those who have gambled in the past year display problem gambling behaviour (Gambling Commission, 2023); and that 3.75% of those using trading apps analogously display problem gambling on those apps (Hayes et al., 2022).

Eight metrics were included with accompanying thresholds in the PPE index (see Annex 4). For example, having £100 or more invested while being in at least 90 days of arrears on a credit product or trading more than once a day on average. We then classified investors into four groups according to the number of PPE thresholds met: 0 (none), 1-2 (low), 3-4 (moderate), and 5+ (high).

We found that 0.35% of traders in our sample showed evidence of highly problematic engagement, while 3.0% did so moderately. Much of this was driven by CFD investors.

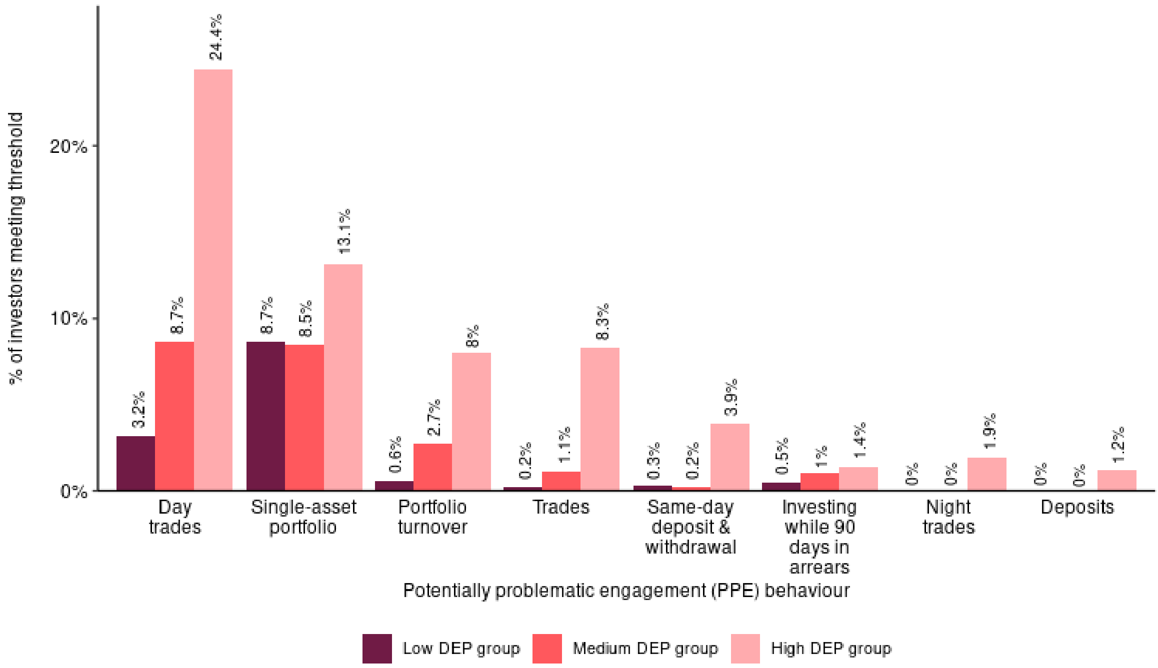
The proportions of investors displaying moderately problematic engagement in the low, medium, and high DEP apps respectively were 0.21%, 0.69% and 5.6% (or 1.5% excluding CFD traders) (Figure 16). For highly problematic engagement, the proportions were 0.002%, none, and 0.68% (or 0.08% excluding CFD traders), respectively.

Figure 16. Number of PPE behaviour thresholds met



The most frequently met criteria across the sample were day trading and holding a portfolio comprising a single (non-fund) asset, which 16% and 10% of users met respectively (Figure 17). The measures most predictive of highly problematic engagement were frequent depositing and night trading. 28% and 26% respectively of investors meeting these criteria met 5 or more of the criteria overall.

Figure 17. Proportion of investors meeting the threshold for each PPE behaviour



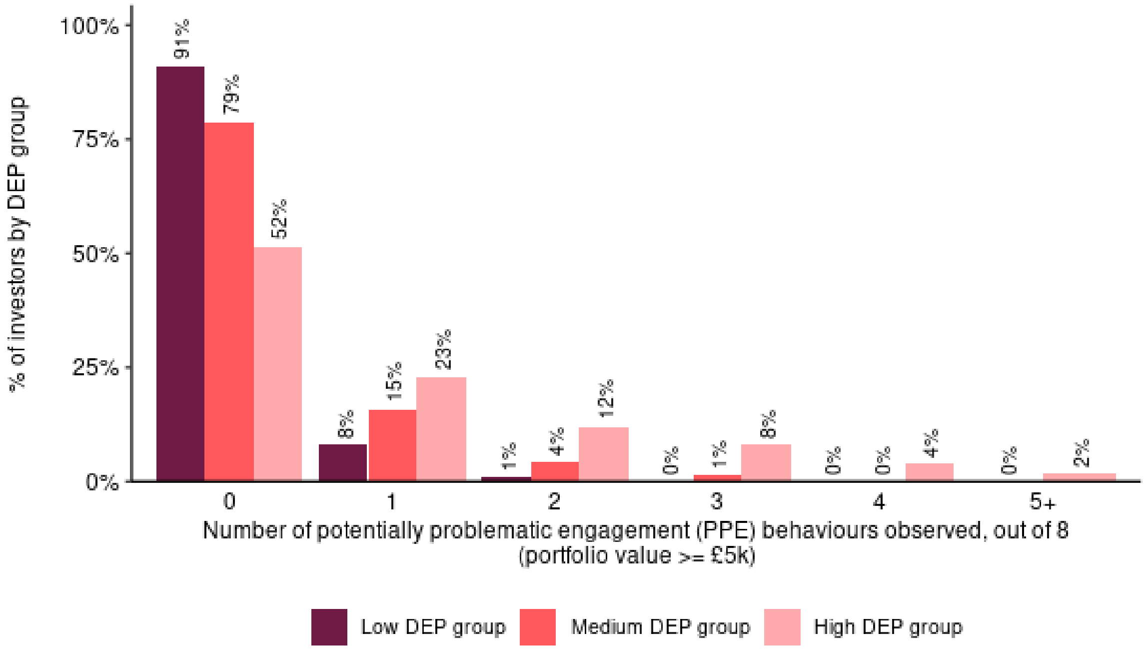
One in four CFD investors demonstrated at least moderate levels of problematic engagement.

Of these, 12% (3% of all CFD investors) additionally met the 'high' criteria. Compared to non-CFD investors, the most commonly met thresholds related to frequency of trading: 66% of CFD users engaged in day trading at least once, 29% averaged at least one trade per day, and 32% had a portfolio turnover rate exceeding seven (one full turnover per month).

For those with portfolios of at least £5000, we found that the proportion meeting the definitions for moderate and high problematic engagement was slightly higher, at 4.1% and 0.6% respectively.

There may be more reason for concern when investors display moderately or highly problematic engagement while having a substantial amount invested in the apps, because this could amplify the scale of potential losses. Figure 18 mirrors Figure 16, but with a filter that only included investors with portfolios worth at least £5000 at their peak. The increase in the proportion of users meeting the definition for moderately problematic engagement for low DEP apps was modest (from 0.21% to 0.28%). However, for medium and high DEP apps, the proportion exhibiting moderately problematic engagement behaviours double (from 0.69% to 1.4% and from 5.6% to 11.9% respectively).

Figure 18. Number of PPE behaviour thresholds met, among investors with portfolios worth at least £5000

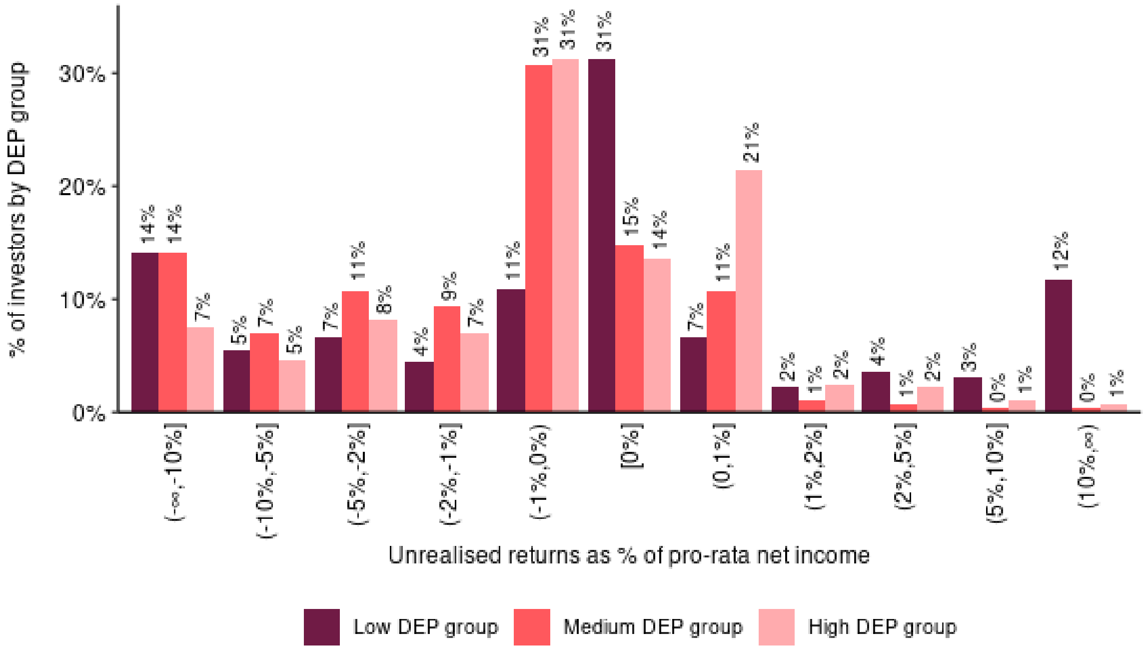


Trading outcomes & DEPs

For two thirds of accounts with any unrealised returns, these returns were negative, driven in part by the market conditions at the time. However, this varied significantly, from 85% for medium DEP apps to 68% for high DEP apps (66% excluding CFD users), and 59% for low DEP apps. For those that used CFDs, the proportion was 79%.

This distribution (relative to pro-rata net income) is shown in Figure 19.

Figure 19. Unrealised returns relative to net income over full 7-month period



To investigate the relationship between DEPs and returns, we ran regression analyses controlling for some key confounding factors – age, gender, and tenure on the app. In our regression (Table 5), both medium and high DEP groups experienced significantly worse unrealised returns relative to income than those on the low DEP apps, by 12.7 and 4.2 percentage points respectively.

Unrealised returns are calculated from the date that each position was opened, so in many cases will be larger in magnitude simply from having been open for longer. On the whole, we would expect this to have a positive effect on unrealised returns, given that the market has generally gone up over time. Unfortunately, we could not see how long positions had been open, so could not explicitly control for this. However, in the regressions we did control for tenure – the length of time that an account had been open. This was a proxy for the maximum possible time that a position could have been open but is of course not a perfect substitute.

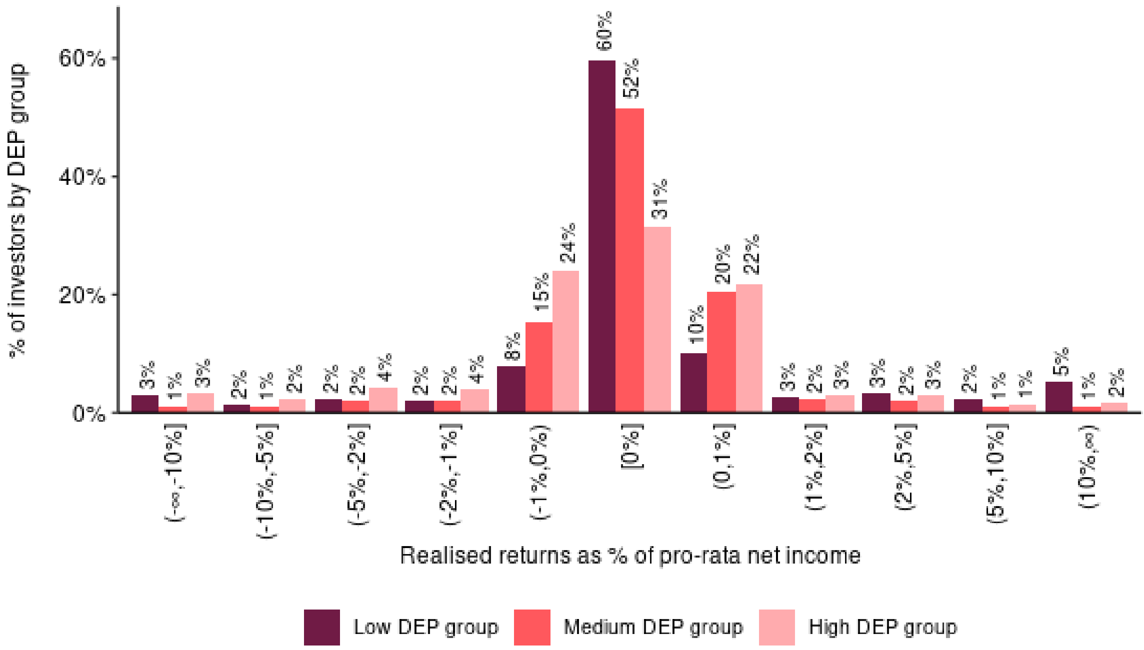
Related to this and working in the opposite direction, unrealised returns will also be smaller in magnitude if an investor is frequently trading into and out of positions. This could be likely to be a major factor contributing to why a larger share of investors using medium DEP groups were left with negative unrealised returns (when compared to investor using high DEP group firms, because the portfolio turnover is generally lower than in the high DEP groups.

We also ran a version of the regression where we included an additional indicator variable for each of CFDs and cryptoassets, coded to 1 if the user has traded or held the product at any point during the study period and was otherwise zero (Table 6). In this regression, the associated detriment of high DEP apps shrunk to 1.3 percentage points and lost statistical significance. The use of CFDs did not have a statistically significant effect on unrealised returns unlike cryptoasset use, which was associated with an average incremental 11.8 percentage point decrease in unrealised returns relative to income.

Exactly half of those accounts that realised any returns, realised gains. Of those that realised returns, significantly fewer high DEP app users (45%, or 48% excluding CFD users) realised gains compared to medium (55%) and low (59%) DEP app users. Of those CFD users that realised returns, only 36% realised gains.

Around two fifths (44%) of accounts had not sold any investments, so did not realise a gain or a loss in our seven-month period. The share of users who had not realised any returns during the 7 months (consistent with a 'buy and hold' strategy) is 60% among the low DEP group, compared to 52% for the medium DEP group and 31% for the high DEP group (Figure 20). Broadening the net slightly, 78%, 87%, and 77% of investors respectively gained or lost less than 1% of their pro rata net income.

Figure 20. Realised returns relative to net income over the full 7-month period



We also looked at the relationship between realised returns and DEP groups, controlling for some key confounding factors (age, gender, and tenure on the app (Table 5). We found that the average realised return (as a proportion of pro rata net income) was significantly lower by 1.3 percentage points for the high DEP apps when compared to low DEP groups. When we looked only at those who realised any returns, this grew to 2.6 percentage points. This is consistent with what we would expect to see if DEPs were resulting in worse returns. The medium DEP group was not significantly different to the low DEP group on this measure.

When we added the CFD and cryptoasset indicators variable as before (Table 6), the realised returns relative to income of high DEP apps users were no longer significantly different to the low DEP app users, but returns were 3.5 percentage points worse for CFD users. This follows the short-term nature of CFDs compared to other instruments - only 3% of CFD traders had no realised returns (i.e., did not close any positions), versus 49% of non-CFD traders.

Investors on the high DEP apps were more likely to experience a 'large loss,' with 10% doing so, compared to 7% and 4% respectively for low and medium DEP apps.

We are particularly interested in realised losses that are likely to be economically significant for the investor. We define a 'large loss' as a realised loss of more than 2% of estimated pro rata net income. Unrealised losses were not considered here due to the variability of time horizons over which they accrued.

Using our regression to control for confounding factors (Table 5), an account being on a high DEP app rather than a low DEP app was associated with a 4.8 percentage point increase in the likelihood of suffering a large loss. In the regression which accounted additionally for product use (Table 6), we found a smaller associated increase in large losses for being on a high DEP app (0.8 percentage points), with a 10 and 0.6 percentage point increase in large losses associated with CFD and cryptoasset use respectively.

Controlling for the other factors, the likelihood of large loss for accounts on medium DEP apps was *lower* than those on low DEP apps, by 1.6 percentage points (Table 5). A contributor to the relatively low figure for medium DEP apps may be the relatively small average portfolio size compared to the other groups, which reduces the chance of a large loss.

Trading outcomes & potentially problematic engagement

Using our PPE measures, we were able to dig deeper into the potential transmission mechanisms between DEPs and trading outcomes. This section covers the relationship between potentially problematic engagement – which we first analysed cumulatively and then on a measure-by-measure basis - and trading outcomes on trading apps.

Controlling for the use of CFD and cryptoassets in these regressions had fairly minimal impact on the associations we see between PPE and returns, both at an individual metric level (Table 10) and when aggregated into an index (Table 8). This supports the hypothesis that our PPE measures reflect the mechanisms through which losses are realised, regardless of the product.

In both forms of PPE regression, we do see a significantly negative relationship between the use of cryptoassets and unrealised returns. This reflects poor cryptoasset market conditions at the time (Figure 2). The poor returns are concentrated in the unrealised category, suggesting that investors are electing not to realise these losses but instead to continue holding the positions open.

Overall, investors that showed signs of problematic engagement had substantially lower unrealised returns (relative to pro rata net income) than those who did not.

Compared to accounts showing no signs of problematic engagement, even a low level of problematic engagement was associated with unrealised returns (relative to pro rata net income) 6 percentage point lower, or 7 percentage points for moderate levels (Table 8). Interestingly, high levels were not associated with a significant difference in unrealised returns. One explanation may be that elevated levels of trading, day trading and portfolio turnover will push unrealised returns towards zero because open positions are not held for long. The corresponding PPE threshold on portfolio turnover, for example, was met by 97% of those exhibiting highly problematic engagement.

Investors with more signs of problematic engagement realised substantially worse returns. The realised returns (relative to pro rata net income) of those showing evidence of highly problematic engagement were lower by 32 percentage points than those showing none.

Similarly, investors exhibiting moderately problematic behaviour realised returns (relative to pro rata net income) that were 9 percentage points lower, and those showing low levels of problematic engagement realised returns (relative to pro rata net income) that were 1 percentage point lower (Table 8).

Realised returns are not distorted by portfolio turnover in the same way as unrealised returns. Instead, elevated level of trading, day trading and portfolio turnover will tend towards increasing the magnitude of realised returns, in either the positive or negative direction. That is because positions are being closed out in order to open new ones. Consequently, we observed an even clearer relationship between a high score on the PPE index (a higher degree of problematic engagement) and poor returns.

Investors with a higher PPE score were more likely to experience a 'large loss,' with those with the highest levels of problematic engagement 64 percentage points more likely to make a large loss than those with a PPE score of zero.

In addition, from our regression (Table 8), we found that investors displaying moderately problematic engagement were 37 percentage points more likely, and investors showing evidence of low problematic engagement were 8 percentage points more likely than those with a PPE score of zero to make large losses.

When analysed discretely, most of our individual PPE measures were associated with poorer outcomes across either unrealised returns, realised returns, or large losses.

We investigated the effect of individual PPE measures on each of our outcomes (Table 7).

Each of our PPE measures - with the exceptions of investing while in at least 90 days of arrears and holding an entirely undiversified portfolio - were associated with poorer outcomes across at least one of: unrealised returns, realised returns or large losses.

When considering unrealised returns (relative to pro rata net income), investors that met the threshold for trading frequency and day trading had substantially poorer outcomes. Those that day traded, for example, had unrealised returns that were 9 percentage points lower. Interestingly, portfolio turnover was associated with unrealised returns that were 8 percentage points higher. Again, this may be due to the fact that unrealised returns are pushed towards zero when open positions are not held for long.

Investors that met the PPE thresholds for trading frequency, night trading, and portfolio turnover had significantly poorer realised returns (relative to pro rata net income) and a significantly higher chance of experiencing a large loss.

The indicator associated with the largest decrease (7 percentage points) in realised returns was frequency of trading - defined as more than one trade per day. Part of this relationship will be mechanical because transaction costs and spreads gradually erode profits. It was also associated with a 3 percentage point increase in the chance of large losses, as shown in Table 7. The indicator associated with the greatest uptick in large losses was day trading, which was associated with a 9 percentage point increase (Table 7).

Night trading, a threshold breached if making one or more trade between 11pm and 6am every week, was associated with a 5 percentage point increase in the chance of large losses.

Investors that deposited and withdrew on the same day or engaged in day trading had a significantly higher chance of realising a large loss (4 percentage points) but did not generally experience lower realised returns.

Figure 21. Proportion of investors realising a large loss across number of trades

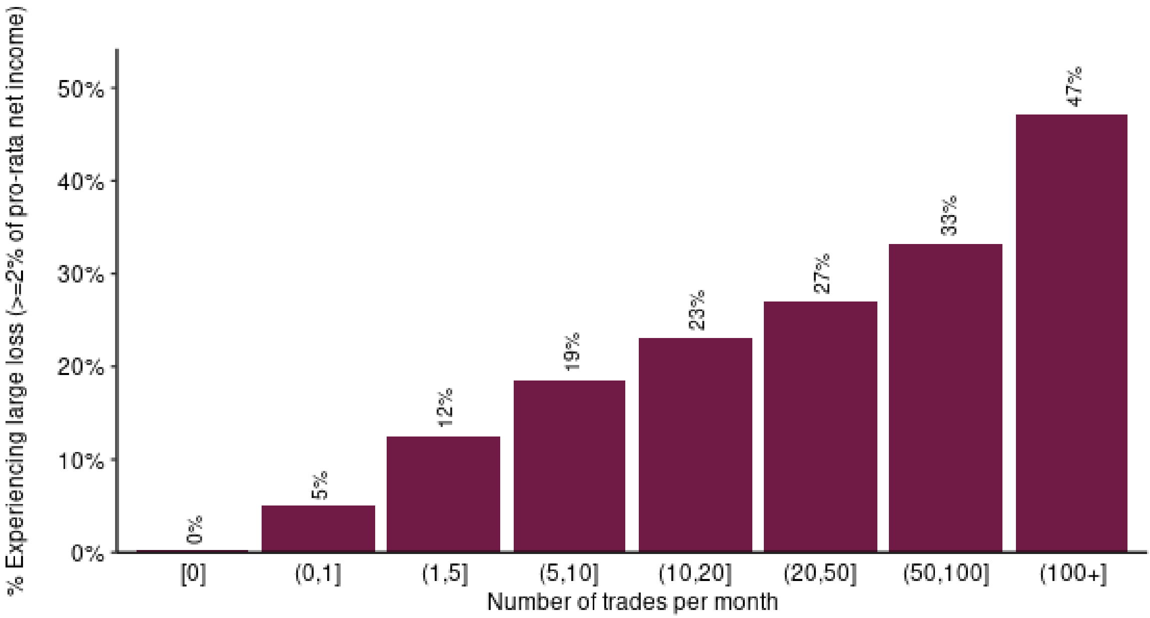
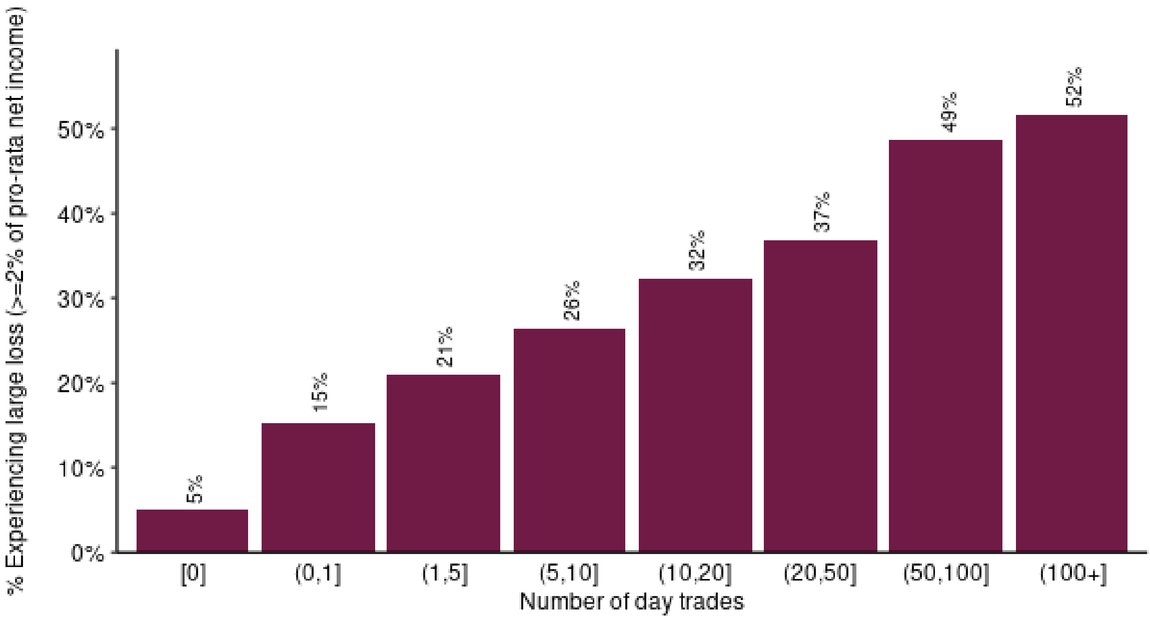


Figure 22. Proportion of investors realising a large loss across number of day trades



5 Discussion

Our earlier online experiment (Gathergood et al., 2024) found that digital engagement practices (DEPs) – like push notifications and points and prize-draws – led to increases in trading and risk-taking in a hypothetical trading setting. This aligned with a range of other research that has shown that DEPs could lead to changes in consumer trading behaviour (e.g., Broihanne, 2023; Chapkovski et al., 2021; Moss, 2022; OSC, 2022).

However, a key remaining question, was to what extent (if it all) do DEPs lead to worse outcomes for consumers on trading apps? That is the primary question we examine in this paper. We believe this is the first study to compare UK investor behaviour across multiple trading apps using observational, consumer transaction level data.

Financial losses

We found that, regardless of how returns are measured (realised returns, unrealised returns, or large losses), investors enjoyed significantly poorer returns on high DEP apps when compared to low DEP apps.

We cannot conclude that DEPs directly cause these worse returns. High DEP apps may be attractive to consumers who, regardless of the DEPs on the app, would have achieved worse returns. Moreover, the evidence suggests that virtually all of the underperformance on high DEP apps could be attributed to trading in cryptoassets and CFD products which – in our sample of firms – were only available on high DEP apps. This could still be consistent with our underlying hypothesis, since one of the key mechanisms through which DEPs could cause harm is by encouraging users to trade in products that are beyond their risk appetite. Unfortunately, our analytical approach and the data available does not allow us to assess whether that is indeed the case.

Potentially problematic engagement

Another key mechanism through which DEPs could be driving poorer outcomes is through more frequent trading, which in turn is related to higher overall engagement. On both counts, we found that engagement and trading was substantially higher on high DEP apps. In an extension of this idea and following previous research - which raised concerns about the extent to which DEPs blur the line between investing and gambling-like behaviours (Hayes et al., 2022) – we explored ‘potentially problematic engagement’ (PPE) on trading apps. We found that, as defined, trading behaviour that is ‘elevated, erratic, or concerning’ was more likely to occur on high DEP apps and was also linked to poorer returns on trading apps. High levels of PPE were particularly prevalent among users of CFDs and cryptoassets. However, even after excluding these users we still found a significant relationship between high DEP apps and PPE, and between PPE and poorer returns.

To our knowledge, this is the first research paper that attempts to look at the behaviour of trading app users using a framework adapted from the academic literature on problem gambling behaviours (e.g., Catania & Griffiths, 2022). We do not present our work on potentially problematic engagement as the final word on this topic, not least because our data across firms was limited and incomplete. Further work is needed to understand the most effective framework and measures for determining from observational data if an investor is engaging in problem gambling-like behaviours when investing.

Financial distress

We found that about 1 in 25 trading app users were investing while in financial distress (most usually because they were in 90+ days of arrears), with a higher proportion of those in the high DEP apps and an even higher proportion trading CFDs or cryptoassets.

We were unable to determine from the data whether financial distress has preceded or followed from investment on a given app. Or in other words, we do not know if consumers who are more likely to suffer financial distress are more likely to choose high DEP apps, or whether the apps with more DEPs lead to higher levels of unsustainable borrowing, or a combination of the two. Another largely unexplored question is the extent to which consumers are borrowing specifically to invest – and the extent to which consumers in financial arrears can be supported to make good financial decisions about whether to maintain investments, as opposed to clearing existing debts.

Trading app users

More broadly, we find that characteristics of the users of trading apps align with previous research, for example, that users of – generally newer - medium and high DEP trading apps tend to be younger and lower earning than those on the low DEP apps, though higher earning than the population as a whole (BritainThinks, 2021). We also find that the gender split on investment apps is stark, with 79% of investors in our sample of trading apps being male. While trading apps with higher DEPs appear to be attracting new types of consumers, this highlights that there may be work to be done to attract more women to investing appropriately.

Further research

In the context of supporting consumers to invest more, it is important to consider whether innovations are delivering good outcomes for the economy as well as for consumers in the longer term. In light of the difficulties in concluding on the drivers of consumer investment outcomes for UK consumers, we hope to see further research on these topics. We encourage firms to reach out to us to collaborate on future research, and assist in building our collective understanding of consumer behaviour and how positive outcomes can be achieved in line with the Consumer Duty (FCA, 2022a, 2022b).

6 References

American Psychiatric Association, 2013. Diagnostic and statistical manual of mental disorders (5th ed.). American Psychiatric Publishing.

Andraszewicz, S., Kaszás, D., Zeisberger, S. and Hölscher, C., 2023. The influence of upward social comparison on retail trading behaviour. Scientific Reports, 13(1), p.22713.

Arnold, M., Pelster, M. and Subrahmanyam, M. G., 2022. Attention triggers and investors' risk-taking. Journal of Financial Economics, 143(2), pp. 846-875.

Arthur, J.N. and Delfabbro, P., 2017. Day traders in South Australia: Similarities and differences with traditional gamblers. Journal of Gambling Studies, 33, pp.855-866.

Arthur, J.N., Williams, R.J. and Delfabbro, P.H., 2016. The conceptual and empirical relationship between gambling, investing, and speculation. Journal of Behavioral Addictions, 5(4), pp.580-591.

Auer, M. and Griffiths, M.D., 2023. Using artificial intelligence algorithms to predict self-reported problem gambling with account-based player data in an online casino setting. Journal of Gambling Studies, 39(3), pp.1273-1294.

Barber, B. M. and Odean, T., 2000. Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. The Journal of Finance, 55(2), pp. 773- 806.

Barber, B.M., Lee, Y.T., Liu, Y.J. and Odean, T., 2010. Do day traders rationally learn about their ability. Unpublished working paper. University of California at Berkeley.

Barber, B.M. and Odean, T., 2013. The behavior of individual investors. Chapter 22 in Constantinides G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance (Vol. 2, pp.1533-1570), Elsevier.

Barber, B.M., Huang, X., Odean, T. and Schwarz, C., 2022. Attention-induced trading and returns: Evidence from Robinhood users. The Journal of Finance, 77(6), pp.3141-3190.

Belgibayeva, A., Croxson, K., Iscenko, Z., Leary, J., and Shaw, J., 2020. Borrower subgroups and the path into distress: commonalities and differences, Available online at: https://www.fca.org.uk/publication/occasional-papers/occasional-paper-49.pdf

Bhamra, H.S. and Uppal, R., 2019. Does household finance matter? Small financial errors with large social costs. American Economic Review, 109(3), pp.1116-1154.

BritainThinks, 2021. Understanding self-directed investors. A summary report of research conducted for The Financial Conduct Authority. Available online at: https://www.fca.org.uk/publication/research/understanding-self-directed-investors.pdf

Broihanne, M.-H., 2023. Gamification and copy trading in finance: an experiment. Available online at: https://www.amf-france.org/fr/sites/institutionnel/files/private/2023-11/article-experience-gamification-novembre-2023_0.pdf

Calvet, L.E., Campbell, J.Y. and Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. Journal of Political Economy, 115(5), pp.707-747.

Catania, M. and Griffiths, M.D., 2022. Applying the DSM-5 criteria for gambling disorder to online gambling account-based tracking data: An empirical study utilizing cluster analysis. Journal of Gambling Studies, 38(4), pp.1289-1306.

Chapkovski, P., Khapko, M. and Zoican, M., 2021. Does gamified trading stimulate risk Taking? Management Science (forthcoming).

Clark, C., 2024. Legalized gambling increases irresponsible betting behavior, especially among low-income populations, UC San Diego Today, Available online at: https://today.ucsd.edu/story/legalized-gambling-increases-irresponsible-betting-behavior-especially-among-low-income-populations

Delfabbro, P., King, D., Williams, J. and Georgiou, N., 2021. Cryptocurrency trading, gambling and problem gambling. Addictive Behaviors, 122, p.107021.

Deterding, S., Dixon, D., Khaled, R. and Nacke, L., 2011, September. From game design elements to gamefulness: defining" gamification". In: Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments (pp. 9-15), Association for Computing Machinery.

Dragicevic, S., Percy, C., Kudic, A. and Parke, J., 2015. A descriptive analysis of demographic and behavioral data from internet gamblers and those who self-exclude from online gambling platforms. Journal of Gambling Studies, 31, pp.105-132.

Elliott, W.B., Gale, B.T. and Hobson, J.L., 2022. The joint influence of information push and value relevance on investor judgments and market efficiency. Journal of Accounting Research, 60(3), pp.1049-1083.

European Securities and Markets Authority (ESMA). Discussion Paper: On MiFID II investor protection topics linked to digitalisation, Available online at: https://www.esma.europa.eu/sites/default/files/2023-12/ESMA35-43-3682_Discussion_Paper_on_MiFID_II_investor_protection_topics_linked_to_digitalisation.pdf

Farghly, F., Hayes, L., Ng, C., and Spohn, M., 2022. Pausing, reading, and reflecting: decision points in high-risk investment consumer journeys, Available online at: https://www.fca.org.uk/publications/research/improving-outcomes-consumers-high-risk-investments

Federal Reserve Board, 2007. Report to the Congress on credit scoring and its effects on the availability and affordability of credit. Available online at: https://www.federalreserve.gov/boarddocs/rptcongress/creditscore/creditscore.pdf

Ferris, J.A. and Wynne, H.J., 2001. The Canadian Problem Gambling Index (pp. 1-59). Ottawa, ON: Canadian Centre on substance abuse. Available online at: https://www.greo.ca/Modules/EvidenceCentre/files/Ferris%20et%20al(2001)The_Canadian_Problem_Gambling_Index.pdf

Financial Conduct Authority, 2019. PS19/18: Restricting contract for difference products sold to retail clients, Available online at: https://www.fca.org.uk/publication/policy/ps19-18.pdf

Financial Conduct Authority, 2021a. InvestSmart: lessons to learn from the GameStop episode, Available online at: https://fca.org.uk/investsmart/lessons-learn-gamestop-episode

Financial Conduct Authority, 2021b. FCA warns that younger investors are taking on big financial risks, Available online at: https://www.fca.org.uk/news/press-releases/fca-warns-younger-investors-are-taking-big-financial-risks

Financial Conduct Authority, 2022a. PS22/19: A new Consumer Duty Feedback to CP21/36 and final rules, Available online at: https://www.fca.org.uk/publication/policy/ps22-9.pdf

Financial Conduct Authority, 2022b. FG22/5: Final non-Handbook Guidance for firms on the Consumer Duty, Available online at: https://www.fca.org.uk/publication/finalised-guidance/fg22-5.pdf

Financial Conduct Authority, 2022c. FCA concerned about problem behaviours linked to trading app design, Available online at: https://www.fca.org.uk/news/press-releases/fca-concerned-about-problem-behaviours-linked-trading-app-design

Financial Conduct Authority, 2022d. InvestSmart: Hype – spot the signs and manage your FOMO, Available online at: https://www.fca.org.uk/investsmart/hype-spot-signs-manage-your-fomo

Financial Conduct Authority, 2023a. Financial Lives 2022: Key findings from the FCA's Financial Lives May 2022 survey, Available online at: https://www.fca.org.uk/publication/financial-lives/financial-lives-survey-2022-key-findings.pdf

Financial Conduct Authority, 2023b. Preparing for the future of Consumer Investments, Available online at: https://www.fca.org.uk/publications/corporate-documents/preparing-future-consumer-investments

Financial Conduct Authority, 2023c. Consumer Investments Strategy - 2 Year Update. Available online at: https://www.fca.org.uk/publications/corporate-documents/consumer-investments-strategy-2-year-update

Financial Conduct Authority, 2023d. InvestSmart: understanding high-risk investments, Available online at: https://www.fca.org.uk/investsmart/understanding-high-risk-investments

Financial Conduct Authority, 2023e. InvestSmart: diversification, Available online at: https://www.fca.org.uk/investsmart/diversification

Financial Conduct Authority, 2024a. FCA keeps trading apps under review over gaming concerns. Available online at: https://www.fca.org.uk/news/press-releases/fca-keeps-trading-apps-under-review-over-gaming-concerns

Financial Conduct Authority, 2024b. InvestSmart: should you invest? Available online at: https://www.fca.org.uk/investsmart/should-you-invest

Financial Conduct Authority, 2024c. FCA finds two-thirds of young investors take less than 24 hours to make investment decisions. Available online at: https://www.fca.org.uk/news/press-releases/fca-finds-two-thirds-young-investors-take-less-24-hours-make-investment-decisions

Financial Conduct Authority, 2025. Financial Lives 2024: Main report from the FCA's Financial Lives May 2024 survey (not yet published).

Finkenwirth, S., MacDonald, K., Deng, X., Lesch, T. and Clark, L., 2021. Using machine learning to predict self-exclusion status in online gamblers on the PlayNow. com platform in British Columbia. International Gambling Studies, 21(2), pp.220-237.

Forrest, D. and McHale, I.G., 2024. The dependence of online gambling businesses on high-spending customers: Quantification and implications. Journal of Gambling Studies, pp.1-22.

GambleAware, 2017. Remote Gambling Research - Interim report on Phase II. Available online at: https://www.gambleaware.org/media/42nbmlic/gamble-aware_remote-gambling-research_phase-2_pwc-report_august-2017-final.pdf

Gambling Commission, 2020. Statistics and research release: problem gambling and gambling-related harms. https://www.gamblingcommission.gov.uk/statistics-and-research/publication/problem-gambling-vs-gambling-related-harms

Gambling Commission, 2021. Statistics and research release: problem gambling screens, Available online at: https://www.gamblingcommission.gov.uk/statistics-and-research/publication/problem-gambling-screens

Gambling Commission, 2023. Statistics and research release: gambling participation and the prevalence of problem gambling survey: Final experimental statistics stage (Step 3), Available online at: https://www.gamblingcommission.gov.uk/statistics-and-research/publication/gambling-participation-and-the-prevalence-of-problem-gambling-survey-final

Gambling Commission, 2024. Measuring the adverse consequences from gambling, Available online at: https://www.gamblingcommission.gov.uk/print/measuring-the-adverse-consequences-from-gambling

Gargano, A. and Rossi, A.G., 2018. Does it pay to pay attention? The Review of Financial Studies, 31(12), pp.4595-4649.

Gathergood, J., Gilchrist, C., Hayes, L., Karapetyan, D., O'Neill, S., and Stewart, N., 2024. Digital engagement practices: a trading apps experiment, Available online at: https://www.fca.org.uk/publications/research-notes/research-note-digital-engagement-practices-trading-apps-experiment

Gilchrist, C., Hayes, L., Ng, C., and Spohn, M., 2022. To certify or not to certify: decision points in the self-certification process, Available online at: https://www.fca.org.uk/publications/research/improving-outcomes-consumers-high-risk-investments

Grant, S.M., Hobson, J.L. and Sinha, R.K., 2024. Digital engagement practices in mobile trading: The impact of color and swiping to trade on investor decisions. Management Science, 70(3), pp.2003-2022.

Gray, C.M., Kou, Y., Battles, B., Hoggatt, J. and Toombs, A.L., 2018, April. The dark (patterns) side of UX design. In: Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-14), Association for Computing Machinery.

Griffiths, M.D., 2012. Internet gambling, player protection, and social responsibility. In: Williams, R., Wood, R., Parke, J. (Eds.), Routledge International Handbook of Internet Gambling (pp. 227-248). Routledge.

Guttman-Kenney, B., Hunt, S., 2017. Preventing financial distress by predicting unaffordable consumer credit agreements: An applied framework. Available online at: https://www.fca.org.uk/publication/occasional-papers/op17-28.pdf

Hayes, L., O'Neill, S., Spohn, M. and Ng, C., 2022. Gaming trading: how trading apps could be engaging consumers for the worse, Available online at: https://www.fca.org.uk/publications/research-articles/gaming-trading-how-trading-apps-could-be-engaging-consumers-worse

Hopfgartner, N., Auer, M., Griffiths, M.D. and Helic, D., 2023. Predicting self-exclusion among online gamblers: An empirical real-world study. Journal of Gambling Studies, 39(1), pp.447-465.

International Organization of Securities Commissions (IOSCO), 2022. Report on Retail Distribution and Digitalisation - Final Report. Available online at: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD715.pdf

International Organization of Securities Commissions (IOSCO), 2024. Consultation Report - Digital Engagement Practices (DEPs). Available online at: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD777.pdf

Louderback, E.R., LaPlante, D.A., Currie, S.R. and Nelson, S.E., 2021. Developing and validating lower risk online gambling thresholds with actual bettor data from a major Internet gambling operator. Psychology of Addictive Behaviors, 35(8), p.921.

Luquiens, A., Tanguy, M.L., Benyamina, A., Lagadec, M., Aubin, H.J. and Reynaud, M., 2016. Tracking online poker problem gamblers with player account - based gambling data only. International Journal of Methods in Psychiatric Research, 25(4), pp.333-342.

Maremount, M., and Berzon, A., (2023, October 11). How often do gamblers really win?, Wall Street Journal, Available online at: https://www.wsj.com/articles/how-often-do-gamblers-really-win-1381514164

Massachusetts Securities Division. 2020. Administrative complaint against Robinhood Financial, LLC. Available online at: https://www.sec.state.ma.us/divisions/securities/download/MSD-Robinhood-Financial-LLC-Complaint-E-2020-0047.pdf

Mathur, A., Kshirsagar, M. and Mayer, J., 2021, May. What makes a dark pattern... dark? design attributes, normative considerations, and measurement methods. In: Proceedings of the 2021 CHI conference on human factors in computing systems (pp. 1-18), Association for Computing Machinery.

Moss, A., 2022. How do brokerages' digital engagement practices affect retail investor information processing and trading? (Doctoral dissertation, The University of Iowa, Iowa City, US). Available online at: https://iro.uiowa.edu/esploro/outputs/doctoral/How-do-brokeragesdigital-engagement-practices/9984362557402771

Newall, P.W. and Weiss-Cohen, L., 2022. The gamblification of investing: How a new generation of investors is being born to lose. International Journal of Environmental Research and Public Health, 19(9), p.5391.

Nieboer, J., 2020. Using online experiments for behaviourally informed consumer policy. FCA Occasional Paper 51. Available online at: https://www.fca.org.uk/publications/occasional-papers/occasional-paper-no-51-using-online-experiments-behaviourally-informed-consumer-policy

Office for National Statistics, 2024a. Population estimates for the UK, England, Wales, Scotland, and Northern Ireland: mid-2022, Available online at:: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2022

Office for National Statistics, 2024b. Accredited official statistics: percentile points from 1 to 99 for total income before and after tax, Available online at: https://www.gov.uk/government/statistics/percentile-points-from-1-to-99-for-total-income-before-and-after-tax

Office for National Statistics, 2024c. Accredited official statistics: distribution of median and mean income and tax by age range and sex, Available online at: https://www.gov.uk/government/statistics/distribution-of-median-and-mean-income-and-tax-by-age-range-and-gender-2010-to-2011

Ontario Securities Commission (OSC), 2022. Digital Engagement Practices in Retail Investing: Gamification and Other Behavioural Techniques. Available online at: https://www.osc.ca/sites/default/files/2022-11/sn_20221117_11-796_gamification-report.pdf

Ontario Securities Commission (OSC), 2024. Digital Engagement Practices: Dark Patterns in Retail Investing. Available online at: https://www.osc.ca/sites/default/files/2024-02/inv-research_20240223_dark-patterns.pdf

Rathi, N., 2024. Investing in outcomes: a regulatory approach to deliver for consumers, markets and competitiveness. 14 March, Morgan Stanley European Financials Conference. Available at: https://www.fca.org.uk/news/speeches/investing-outcomes-regulatory-approach-deliver-consumers-markets-and-competitiveness

Securities and Exchange Commission (SEC), 2021. Release Nos. 34-92766 Request for information and comments on broker-dealer and investment adviser digital engagement practices, related tools and methods, and regulatory considerations and potential approaches; information and comments on investment adviser use of technology to develop and provide investment advice. Available online at: https://www.sec.gov/files/rules/other/2021/34-92766.pdf

Shefrin, H. and Statman, M., 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of Finance, 40(3), pp.777-790.

Sunstein, C. R., 2022. Sludge audits. Behavioural Public Policy, 6(4).

Sunstein, C. R., 2018. Sludge and ordeals. Duke LJ, 68, 1843.

Thaler, R. H., 2018. Nudge, not sludge. Science, 361(6401), 431-431.

Taylor, W., McCarthy, D. and Wilbur, K.C., 2024. Online gambling policy effects on tax revenue and irresponsible gambling. Available at SSRN 4856684.

Ukhov, I., Bjurgert, J., Auer, M. and Griffiths, M.D., 2021. Online problem gambling: A comparison of casino players and sports bettors via predictive modeling using behavioral tracking data. Journal of Gambling Studies, 37(3), pp.877-897.

Annex 1: Trading app (TA) dataset

The table below describes the outlines of the trading apps dataset. In some limited cases, variables listed below were missing because firms were not able to provide the data requested.

Table 1: Outline of the five related datasets

Dataset	Description	Key variables	Time period
Customer demographics data	Data on the demographics of account holder	Date account opened; demographic variables (DOB, postcode, gender, income etc)	
Trade data	Data on each trade conducted	Trade type (buy, sell, short sale); what was traded (instrument name, CFI & ISIN code, category of instrument e.g., fund, cryptoasset etc.); price and charges on the trade; date and time of trade	Time period 1, 2 & 3
Portfolio holdings data	Data on each accounts portfolio and returns	Portfolio value at start and end of time period; for each instrument in the portfolio - name, category, price, and value of the instrument at start and end of time period; realised and unrealised returns from the portfolio for the time period; gross, net of forex charges and net of all transaction charges for each return	Time period 1, 2 & 3
App usage or app session data	Data on sessions, deposits and withdrawals made on the app	Session time and date; whether a trade was made; deposit data (how many, method used, amount and time); withdrawal data (how many, amount, and time);	Time period 1, 2 & 3
Daily returns data	Realised and unrealised	Realised and unrealised gross returns for each day in the time period	Only covers 1

	returns data for each day		May – 30 June 2022

Annex 2: Sample description

Classification algorithm for gender

Gender was missing for 37% of our sample. This is predominantly due to some firms not collecting data on gender for all of their customers or, in some limited cases, customers selecting 'prefer not to say' when asked about their gender. We, therefore, used a classification algorithm to fill the gaps where data was not provided.

The gender classification algorithm works by assigning genders to names based on the frequency of name-gender associations in large scale data sets. From this, it provides a predicted gender, a probability associated with this prediction, and the sample size underlying the calculation. We used this to fill in gaps in the gender field for individuals where stated gender was missing or "prefer not to say", provided that the name was not very rare in the UK population (fewer than 10 uses) and the probability of correct prediction was greater than or equal to 90%. Testing the algorithm's predictions against the data with non-missing values for gender, the predictions are correct in 99% of cases.

The algorithm is able to classify all but 12% of our sample with a missing gender (equivalent to 4.5% of our total sample), based on the parameter thresholds we used. This means we have a gender or predicted gender for 95.5% of our sample. When we use gender as a covariate in regression in this paper, we exclude those 4.5% investors for whom we do not have a gender.

Sample comparisons

We compare those in our sample with and without a CRA match in Table 2 below. We find that, across key demographic variables and behaviour on the trading apps themselves, investors with and without a CRA match are not substantially different.

Table 2: CRA sample comparison

Metric		TA data linked to CRA	TA data not linked to CRA
Gender	**% Male**	76%	76%
Age	**Median**	33	32
	Mean	35	35
Peak portfolio value	**Median**	£20	£20
	Mean	£12,358	£15,254
Tenure on app	**Median**	2.0 years	2.0 years
	Mean	2.6 years	2.6 years
Number of trades	**Median**	0 per month	0 per month
	Mean	4.0 per month	4.0 per month
% ‘Active Traders’		42%	43%
Filtered on active traders only:			
Gender	**% Male**	80%	77%
Age	**Median**	36	35
	Mean	38	38
Peak portfolio value	**Median**	£2,566	£2,807
	Mean	£29,413	£35,505
Tenure on app	**Median**	2.3 years	2.2 years
	Mean	3.3 years	3.3 years
Number of trades	**Median**	0.43 per month	0.43 per month
	Mean	9.1 per month	8.9 per month

After excluding investors without an active account, we have 176,159 investors within our sample. When we are looking at those for who we had a credit file match, the sample is 106,961. We compare the demographics and credit position of those investors that have ‘active accounts’ and those that have inactive accounts in Table 3.

Table 3: Active trader sample comparison

Metric		Active traders	Others
Gender	**% Male**	79%	73%
Age	**Median**	36	31
	Mean	38	33
Peak portfolio value	**Median**	£2,656	£0
	Mean	£31,806	£8
Tenure on app	**Median**	2.3 years	1.8 years
	Mean	3.3 years	2.0 years
Number of trades	**Median**	0.43 per month	0 per month
	Mean	9.0 per month	0.24 per month
% Linked to CRA	**%**	61%	62%
Filtered on investors linked to CRA only:			
Estimated annual net income	**Median**	£36,477	£27,204
	Mean	£48,937	£35,590
% in financial distress	**%**	3.8%	18.2%

Annex 3: Regression results

Table 4: Regressions per PPE indicator

	Dependent variable								
	Trades	Night trades	Deposits	Same day deposit/ withdrawal	Day trades	Portfolio turnover	Investing while in 90 days of arrears	Single asset portfolio	#PPEs
	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit	OLS
DEP group (ref: Low DEP group)									
Medium DEP group	0.009*** (0.001)	0.0001 (0.0001)	-0.0005*** (0.0001)	-0.001* (0.0003)	0.055*** (0.002)	0.022*** (0.001)	0.005*** (0.001)	-0.002 (0.002)	0.087*** (0.006)
High DEP group	0.081*** (0.001)	0.019*** (0.0004)	0.011*** (0.0004)	0.036*** (0.001)	0.213*** (0.002)	0.075*** (0.001)	0.009*** (0.0005)	0.044*** (0.002)	0.488*** (0.004)
Observations	188,910	188,910	188,910	188,910	188,910	188,910	188,910	188,910	188,910
R^2									0.084
Adjusted R^2									0.083
Residual Std. Error									0.772
F Statistic									8,606***
Log Likelihood	-30,343	-9,485	-6,420	-17,520	-70,732	-32,703	-10,524	-64,588	
Akaike Inf. Crit.	60,693	18,976	12,846	35,046	141,470	65,413	21,055	129,183	

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 5: Regressions with DEP groups

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-3.31* (1.52)	-0.23 (0.46)	-3.54* (1.70)	-1.04*** (0.29)
35-44	-4.40** (1.59)	-0.70 (0.48)	-5.10** (1.78)	-0.29 (0.31)
45-54	0.09 (1.76)	0.47 (0.53)	0.56 (1.98)	0.67 (0.35)
55-64	5.26* (2.07)	0.09 (0.63)	5.35* (2.32)	3.12*** (0.45)
65+	18.71*** (2.80)	5.74*** (0.85)	24.44*** (3.14)	5.47*** (0.68)
Gender (ref: Female)				
Male	-2.10 (1.14)	-0.39 (0.35)	-2.48 (1.28)	3.57*** (0.20)
Tenure (ref: Less than 1 year)				
1-2 years	-1.56 (1.58)	-0.35 (0.48)	-1.91 (1.78)	4.13*** (0.24)
2-3 years	-1.84 (1.63)	-0.20 (0.49)	-2.05 (1.83)	5.38*** (0.25)
3+ years	10.45*** (1.71)	1.92*** (0.52)	12.38*** (1.92)	6.36*** (0.29)
DEP group (ref: Low DEP group)				
Medium DEP group	-12.74*** (1.52)	-0.20 (0.46)	-12.94*** (1.70)	-1.64*** (0.25)
High DEP group	-4.23*** (1.10)	-1.30*** (0.33)	-5.52*** (1.23)	4.83*** (0.22)
Observations	91,507	91,507	91,507	91,507
R^2	0.005	0.002	0.005	
Adjusted R^2	0.005	0.002	0.005	
Residual Std. Error	137.27	41.55	154.11	
F Statistic	42.31***	17.49***	245.94***	
Log Likelihood				-22,176
Akaike Inf. Crit.				50,377

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

Table 6: Regressions with DEP groups, CFD indicator, and cryptoasset indicator

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-2.65 (1.52)	-0.18 (0.46)	-2.83 (1.71)	-1.13*** (0.30)
35-44	-3.08 (1.60)	-0.52 (0.48)	-3.60* (1.79)	-0.77* (0.31)
45-54	1.59 (1.77)	0.65 (0.54)	2.23 (1.98)	0.19 (0.35)
55-64	6.55** (2.07)	0.23 (0.63)	6.78** (2.33)	2.74*** (0.45)
65+	19.80*** (2.80)	5.83*** (0.85)	25.63*** (3.14)	5.22*** (0.67)
Gender (ref: Female)				
Male	-1.81 (1.14)	-0.30 (0.35)	-2.11 (1.29)	3.28*** (0.20)
Tenure (ref: Less than 1 year)				
1-2 years	-1.22 (1.58)	-0.45 (0.48)	-1.67 (1.78)	4.29*** (0.23)
2-3 years	-4.91** (1.67)	-0.73 (0.50)	-5.64** (1.87)	6.60*** (0.26)
3+ years	10.35*** (1.71)	1.83*** (0.52)	12.18*** (1.92)	6.31*** (0.27)
DEP group (ref: Low DEP group)				
Medium DEP group	-12.78*** (1.52)	-0.20 (0.46)	-12.98*** (1.70)	-2.08*** (0.30)
High DEP group	1.32 (1.29)	-0.07 (0.39)	1.25 (1.45)	0.83** (0.27)
CFD usage (ref: CFDs not used)				
CFD user	-1.24 (1.62)	-3.46*** (0.49)	-4.70** (1.82)	9.97*** (0.25)
Cryptoasset usage (ref: cryptoassets not used)				
Cryptoasset user	-11.80*** (1.49)	-0.88 (0.45)	-12.68*** (1.68)	0.59* (0.27)
Observations	91,507	91,507	91,507	91,507
R^2	0.006	0.003	0.006	
Adjusted R^2	0.006	0.003	0.006	
Residual Std. Error	137.22	41.54	154.04	
F Statistic	41.17***	19.66***	44.82***	
Log Likelihood				-24,300
Akaike Inf. Crit.				48,627

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

Table 7: Regressions with PPE scores

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-3.26* (1.52)	-0.16 (0.46)	-3.42* (1.70)	-1.15*** (0.29)
35-44	-3.85* (1.59)	-0.39 (0.48)	-4.24* (1.78)	-1.11*** (0.30)
45-54	0.91 (1.76)	0.84 (0.53)	1.75 (1.97)	-0.32 (0.34)
55-64	6.18** (2.06)	0.46 (0.62)	6.64** (2.31)	2.26*** (0.42)
65+	19.83*** (2.79)	5.98*** (0.84)	25.81*** (3.13)	4.95*** (0.63)
Gender (ref: Female)				
Male	-1.73 (1.14)	-0.13 (0.35)	-1.86 (1.28)	2.51*** (0.21)
Tenure (ref: Less than 1 year)				
1-2 years	-1.67 (1.58)	-0.34 (0.48)	-2.01 (1.78)	4.05*** (0.22)
2-3 years	-0.40 (1.62)	-0.25 (0.49)	-0.65 (1.82)	5.60*** (0.24)
3+ years	13.30*** (1.65)	1.93*** (0.50)	15.23*** (1.85)	6.87*** (0.26)
PPE thresholds met (ref: threshold not met)				
Trades	-6.83* (2.75)	-6.77*** (0.83)	-13.60*** (3.09)	3.20*** (0.32)
Night trades	-2.75 (5.05)	-5.88*** (1.53)	-8.64 (5.67)	4.50*** (0.52)
Deposits	-2.55 (6.00)	-4.29* (1.81)	-6.84 (6.73)	1.23 (0.69)
Same-day deposit and withdrawal	3.73 (3.34)	-1.51 (1.01)	2.23 (3.75)	3.62*** (0.41)
Day trades	-9.23*** (1.56)	-0.46 (0.47)	-9.69*** (1.75)	9.02*** (0.23)
Portfolio turnover	8.01** (2.55)	-4.26*** (0.77)	3.75 (2.86)	6.16*** (0.28)
Investing while 90 days in arrears	0.13 (3.69)	0.11 (1.11)	0.24 (4.14)	1.13 (0.60)
Single-asset portfolio	-1.46 (1.48)	-0.65 (0.45)	-2.10 (1.67)	-0.49 (0.30)
Observations	91,507	91,507	91,507	91,507
R^2	0.005	0.006	0.006	
Adjusted R^2	0.005	0.006	0.006	
Residual Std. Error	137.29	41.48	154.06	
F Statistic	26.90***	30.80***	33.08	
Log Likelihood				-22,413
Akaike Inf. Crit.				44,861

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

Table 8: Regressions with PPE scores, CFD indicator, and cryptoasset indicator

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-2.99* (1.52)	-0.14 (0.46)	-3.13 (1.70)	-1.17*** (0.29)
35-44	-3.32* (1.59)	-0.34 (0.48)	-3.67* (1.79)	-1.15*** (0.30)
45-54	1.48 (1.76)	0.89 (0.53)	2.37 (1.97)	-0.36 (0.34)
55-64	6.54** (2.06)	0.50 (0.62)	7.04** (2.32)	2.25*** (0.43)
65+	19.98*** (2.79)	6.01*** (0.84)	25.99*** (3.13)	4.98*** (0.63)
Gender (ref: Female)				
Male	-1.42 (1.15)	-0.11 (0.35)	-1.53 (1.29)	2.49*** (0.21)
Tenure (ref: Less than 1 year)				
1-2 years	-1.19 (1.58)	-0.29 (0.48)	-1.48 (1.78)	4.01*** (0.22)
2-3 years	-1.54 (1.64)	-0.32 (0.50)	-1.86 (1.84)	5.75*** (0.25)
3+ years	12.85*** (1.66)	1.91*** (0.50)	14.76*** (1.86)	6.93*** (0.26)
PPE thresholds met (ref: threshold not met)				
Trades	-6.63* (2.79)	-6.84*** (0.84)	-13.48*** (3.13)	3.02*** (0.32)
Night trades	-1.89 (5.08)	-5.90*** (1.53)	-7.79 (5.70)	4.29*** (0.53)
Deposits	-3.03 (6.00)	-4.29* (1.81)	-7.33 (6.73)	1.34 (0.69)
Same-day deposit and withdrawal	3.46 (3.34)	-1.53 (1.01)	1.93 (3.75)	3.66*** (0.41)
Day trades	-9.09*** (1.63)	-0.54 (0.49)	-9.63*** (1.83)	8.85*** (0.24)
Portfolio turnover	6.62* (2.61)	-4.47*** (0.79)	2.15 (2.93)	6.08*** (0.29)
Investing while 90 days in arrears	0.75 (3.69)	0.14 (1.11)	0.89 (4.14)	1.08 (0.60)
Single-asset portfolio	-1.32 (1.48)	-0.63 (0.45)	-1.95 (1.67)	-0.50 (0.30)
CFD usage (ref: CFDs not used)				
CFD user	4.86** (1.87)	0.72 (0.57)	5.58** (2.10)	0.28 (0.29)
Cryptoasset usage (ref: cryptoassets not used)				
Cryptoasset user	-7.46*** (1.31)	-0.57 (0.40)	-8.03*** (1.47)	0.54* (0.24)
Observations	91,507	91,507	91,507	91,507
R^2	0.005	0.006	0.006	
Adjusted R^2	0.005	0.006	0.006	
Residual Std. Error	137.26	41.48	154.04	
F Statistic	25.82***	27.78***	31.23***	
Log Likelihood				-22,408
Akaike Inf. Crit.				44,857

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

Table 9: Regressions with individual PPE indicators

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-3.34* (1.52)	-0.19 (0.46)	-3.53* (1.70)	-1.29*** (0.30)
35-44	-3.99* (1.59)	-0.44 (0.48)	-4.43* (1.78)	-1.17*** (0.31)
45-54	0.84 (1.76)	0.82 (0.53)	1.66 (1.97)	-0.51 (0.34)
55-64	6.11** (2.06)	0.41 (0.62)	6.52** (2.31)	1.92*** (0.43)
65+	19.78*** (2.78)	5.94*** (0.84)	25.72*** (3.13)	4.64*** (0.64)
Gender (ref: Female)				
Male	-1.83 (1.14)	-0.19 (0.35)	-2.02 (1.28)	2.80*** (0.21)
Tenure (ref: Less than 1 year)				
1-2 years	-1.93 (1.58)	-0.43 (0.48)	-2.36 (1.77)	4.09*** (0.22)
2-3 years	-0.83 (1.62)	-0.36 (0.49)	-1.19 (1.81)	5.98*** (0.24)
3+ years	12.96*** (1.65)	1.89*** (0.50)	14.85*** (1.85)	6.95*** (0.26)
Number of PPE thresholds met (ref: None)				
1-2 (Low)	-5.97*** (1.09)	-1.38*** (0.33)	-7.36*** (1.22)	8.01*** (0.25)
3-4 (Moderate)	-6.89** (2.62)	-8.69*** (0.79)	-15.58*** (2.94)	37.38*** (0.91)
5+ (High)	-8.62 (7.34)	-31.98*** (2.22)	-40.59*** (8.24)	64.29*** (2.40)
Observations	91,507	91,507	91,507	91,507
R^2	0.005	0.005	0.006	
Adjusted R^2	0.005	0.005	0.006	
Residual Std. Error	137.30	41.48	154.09	
F Statistic	35.82***	42.00***	43.85***	
Log Likelihood				-23,149
Akaike Inf. Crit.				46,324

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

Table 10: Regressions with individual PPE indicators, CFD indicator, and cryptoasset indicator

	Dependent variable			
	Unrealised returns (% of net income)	Realised returns (% of net income)	Total returns (% of net income)	Large loss (>=2% of net income)
	OLS	OLS	OLS	Logit
Age (ref: 18-24)				
25-34	-3.06* (1.52)	-0.17 (0.46)	-3.23 (1.70)	-1.27*** (0.29)
35-44	-3.43* (1.59)	-0.39 (0.48)	-3.81* (1.79)	-1.21*** (0.31)
45-54	1.43 (1.76)	0.86 (0.53)	2.29 (1.97)	-0.46 (0.34)
55-64	6.45** (2.06)	0.41 (0.62)	6.86** (2.31)	2.12*** (0.43)
65+	19.86*** (2.79)	5.91*** (0.84)	25.77*** (3.13)	5.00*** (0.64)
Gender (ref: Female)				
Male	-1.48 (1.15)	-0.14 (0.35)	-1.62 (1.29)	2.69*** (0.21)
Tenure (ref: Less than 1 year)				
1-2 years	-1.47 (1.58)	-0.41 (0.48)	-1.88 (1.78)	4.08*** (0.22)
2-3 years	-2.15 (1.63)	-0.53 (0.49)	-2.68 (1.83)	6.33*** (0.24)
3+ years	12.39*** (1.66)	1.80*** (0.50)	14.19*** (1.86)	7.14*** (0.26)
Number of PPE thresholds met (ref: None)				
1-2 (Low)	-5.43*** (1.13)	-1.19*** (0.34)	-6.62*** (1.26)	6.95*** (0.25)
3-4 (Moderate)	-5.94* (2.88)	-8.03*** (0.87)	-13.96*** (3.23)	28.43*** (0.98)
5+ (High)	-8.33 (7.48)	-31.24*** (2.26)	-39.58*** (8.40)	53.57*** (2.79)
CFD usage (ref: CFDs not used)				
CFD user	2.91 (1.76)	-0.52 (0.53)	2.39 (1.97)	3.79*** (0.27)
Cryptoasset usage (ref: cryptoassets not used)				
Cryptoasset user	-7.85*** (1.31)	-0.77 (0.40)	-8.62*** (1.47)	0.63** (0.24)
Observations	91,507	91,507	91,507	91,507
R^2	0.005	0.006	0.006	
Adjusted R^2	0.005	0.005	0.006	
Residual Std. Error	137.28	41.48	154.06	
F Statistic	33.29***	36.48***	40.09***	
Log Likelihood				-23,017
Akaike Inf. Crit.				46,064

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

Annex 4: Potentially problematic engagement

'Potentially problematic engagement' (PPE) is a term we use to capture elevated, erratic, or concerning trading behaviour on an app. To assess PPE, we set out eight engagement metrics - each with a threshold - that we reasoned was related to problem gambling and could be associated with poor returns (Table 11). Under this framework, meeting the threshold for a given metric would indicate potentially problematic engagement. Meeting the thresholds for three to four metrics was considered 'moderately problematic engagement' and meeting the thresholds for five or more metrics was considered 'highly problematic engagement.'

We were motivated to explore such an approach by the academic literature on gambling and in particular the literature on 'problem gambling' and its operationalisation in observational datasets. We expand on this below.

Comparisons between gambling and investing

The key difference between gambling and investing, is that gambling is generally loss making for gamblers, whereas investing – over a long enough time horizon and across a diversified portfolio – is highly likely (although not guaranteed) to lead to positive returns for investors.

While some gamblers may make money, they are few. For example, analysis from a stratified sample of 140,000 UK consumers across a multi-operator dataset, found that approximately 90% of gamblers lost money over a 12-month period (Forrest & McHale, 2024). In an analysis of a panel of 700,000 gamblers in the US over a five-year period, an estimated 96% of gamblers lost money (Taylor, McCarthy & Wilbur, 2024; Clark, 2024). Other analysis from a sample of around 4,000 gamblers that wagered at least four times between 2005 and 2007 on websites run by a major European online gambling company, found that 89% of gamblers lost money (Maremount & Berzon, 2023).

The returns from investment are, of course, dependent on a range of factors, including asset allocation, fees, and market conditions. However, over a sufficiently long time horizon, the majority of investors can enjoy the tendency for markets - and hence their investments - to rise in value. For example, in the ten years to January 2025, the FTSE 100 returned around 21% and the S&P500 returned around 187%. In one of the few longer-term studies of retail investors returns, Barber and Odean (2000) found that, of the approximately 65,000 households with an account at a large discount broker during 1991 to 1996, the *average* household earned an annual return of around 16%.

Nonetheless, comparisons have been drawn between specific forms of investing and gambling as well as investors and gamblers (Newall & Weiss-Cohen, 2022; Delfabbro, King, Williams & Georgiou, 2021). For example, short expected return timeframes and high volatility are features that are common across gambling and some forms of investing – namely day trading of equities and cryptoassets (Delfabbro, King, Williams & Georgiou, 2021). In addition, the evidence suggests that people who gamble are more likely to engage in riskier trading strategies, such as day trading (Delfabbro, King, Williams & Georgiou, 2021; Arthur & Delfabbro, 2017), high frequency trading (Arthur, Delfabbro, & Williams, 2016), and trading in riskier products such as cryptoassets (Delfabbro, King, Williams & Georgiou, 2021). Similarities have been found between investors and gamblers in motivational and personality attributes (Arthur, Williams & Delfabbro, 2016) as well as in susceptibility to similar cognitive biases (Barber & Odean, 2001).

Problem gambling

Problem gambling is 'gambling to a degree that compromises, disrupts, or damages family, personal or recreational pursuits' (Gambling Commission, 2020). It is often assessed using the Problem Gambling Severity Index (PGSI) (Ferris & Wynne, 2001; Gambling Commission, 2021), a 9-question self-reported psychological scale. Questions in the PGSI include:

- 'Have you bet more than you could really afford to lose?'
- 'Have you borrowed money or sold anything to get money to gamble?'
- 'Has your gambling caused any financial problems for you or your household?'

The possible answers to questions on the PGSI are: 'never,' 'sometimes,' 'most of the time' and 'almost always,' which respectively correspond to scores of 0, 1, 2 and 3. The scores for each question are summed to give an overall score. An overall score of 8 or more represents problem gambling and a score of 3-7 indicates moderate risk gambling. Research on gambling in the UK (Gambling Commission, 2023) finds that 2.5% of respondents, approximately 4.1% of all those who have gambled in the last year, display problem gambling – as evidenced by a score of 8+ on the PGSI. A further 3.5% of respondents, approximately 5.5% of those who gambled in the last year, participated in 'moderate risk' gambling.

Hayes et al. (2022) adapted the PGSI for use in an investment context – replacing mentions of 'gamble/gambled/gambling' or 'bet/bet/betting' with 'invest/invested/investing'. The research found that, in a survey of users of five prominent investment apps, levels of problem gambling behaviour associated with investment (as measured by scoring 8+ on the amended PGSI) was 3.75%, approximately equal to the 4.1% of gamblers who score 8+ on the traditional PGSI (Gambling Commission, 2023). In addition, they found that the proportion of users 'at-risk' of problem gambling behaviours associated with investment (as measured by scoring 3+ on the amended PGSI) was significantly higher on apps with more DEPs.

Identifying problem gambling in observational datasets

The psychological scales commonly used to assess problem gambling, such as the PGSI, require respondents to answer questions about their gambling behaviour and its consequences. As such, they rely on being able to survey consumers. However, surveying consumers is not always possible and there may be some other limitations, notably the reliance on self-reporting which may lead to misreporting and, in particular, under-reporting (Gambling Commission, 2024).

For that reason, attempts have been made in the gambling literature to identify problem gambling in administrative datasets. One approach to this problem is to find proxies or indicators in administrative datasets that might match the criteria in problem gambling scales. For example, Catania and Griffiths (2022) sought behavioural indicators that could operationalise the nine criteria for 'gambling disorder' in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013). Using a two-step clustering algorithm, they established that the following indicators, when higher than average, were relevant in defining a 'financially vulnerable gambler' cluster: number (and increase of) daily deposits over time, number of hours (and active days) spent gambling, and number of registered credit cards on an account.

Another common approach has been to analyse what factors are predictive of problem-gambling-related exclusion from gambling platforms. Exclusion may include self-exclusion, where an individual voluntarily removes themselves from a platform. Exclusion may also include staff-exclusion, where an individual is informed that they are being temporarily or permanently removed from the platform due to the provider's concerns.

Using such an approach, Ukhov et al. (2021) found that predictive factors for exclusion – although they varied between sports betting and casino play – included high frequency of wagers, high amount spent, larger volume of losses, longer duration of sessions. In their sample of Canadian online gamblers, Finkenwirth et al. (2021) found that the variance in money bet per session was the factor most predictive of exclusion. In a sample of more than 25,000 online gamblers across Europe, Hopfgartner et al. (2022) found that when the following features were elevated, exclusion was more likely: number of deposits per session, number of different types of games played, number of different deposit payment methods, number of previous voluntary limit changes, and number of self-exclusions.

Another approach has been to predict problem gambling, as measured by the PGSI and other scales, by linked transactional data on gambling. In a sample of poker players, Luquiens et al. (2016) found that responses on the PGSI could be explained – in part - by the frequency of bets in a single session and depositing within a 12-hour period, as well as elevated losses. In a sample of European online gamblers, Auer and Griffiths (2023) found that the features most predictive of self-reported problem gambling were frequent depositing within a session and regularly depleting the account entirely. Using a slightly different scale, the Brief Biosocial Gambling Screen (BBGS), Louderback et al. (2021) found that betting volume per month, the percentage of the annual income bet, daily variability in the amount bet and financial losses per month could be used to set thresholds for low-risk gambling.

Operationalising potentially problematic engagement in trading apps data

Unlike the studies above, we did not have reliable data on problem gambling-related exclusion from the trading apps in our sample, and our data was not linked to problem gambling survey data. Therefore, we implemented an approach that more closely follows efforts to operationalise gambling-like criteria (e.g., Catania & Griffiths, 2022). The measures we selected are outlined in Table 11.

Table 11: Potentially problematic engagement (metrics and thresholds)

Behaviour	Specific metric	Threshold
Frequency of trading	Count of trades	>1 a day on average
Portfolio turnover	How often funds are withdrawn from their existing positions and reinvested*	>= 7
Day-trading	Opening and closing a position within the same calendar day	Occurring at least once in the time period
Night-time trading	Count of trades initiated at between 11pm and 6am	>1 for every 5 nights on average
Frequent depositing	Count of ad hoc deposits	>1 a week on average
Same-day deposit and withdrawal	Ad hoc deposit and withdrawal within the same calendar day	Occurring at least once in the time period
No portfolio diversification	Maximum number of unique non-fund assets held at a time	Never observed exceeding 1
Investing while in 90 days of arrears	Portfolio value (excluding SIPPs) exceeding £100 in the same month as being in at least 90 days of arrears on a credit product	Occurring at least once in the time period

***Notes on portfolio turnover:** a simple example to demonstrate portfolio turnover would be a user that starts with £100 of asset A, sells all of this, and buys £100 of asset B. They would have a 'turnover' of 1. If the user then sold all of their asset B holdings and bought instead £100 of asset C, their 'turnover' would be 2. In practice, we estimate portfolio turnover in a three-step process. Firstly, we (1) calculate the total amount spent opening positions. We then (2) divide that by whichever is higher out of the total amount of money deposited to the account or the mean portfolio value across the six dates (01/11/2021, 31/12/2021, 01/03/2022, 30/06/2022, 01/11/2022, 30/11/2022) for which we have portfolio value. Lastly, we (3) take as our portfolio turnover, the minimum of the figure calculated in (2) and the number of transactions made to close positions. For example, if a consumer has (1) spent £400 opening positions, on the basis of £100 of deposits and the average value in the portfolio is £100, then in (2) we would get a figure of 4. Further, if the consumer had made only 2 transactions to close positions, then we would take the minimum between 4 and 2 and set the (3) portfolio turnover to 2. Our estimation approach is therefore conservative to allow for the time gaps in our data and also in the case of some firms the gaps in deposit data.

Some of the measures are similar to those in a gambling context. For example, a 'preoccupation' with gambling - essentially persistently thinking about gambling - is often operationalised by the amount of time an individual spends gambling and the number of bets made (Griffiths, 2012). While missing data from some firms prevents us from including time spent in our index, we can look at the frequency of trading, portfolio turnover and day trading. These measures are more useful than total spend because unlike gambling there is no inherent reason to be concerned about investing large sums. Elevated levels of trading, however, while indicative of preoccupation, is also likely to be associated with poorer returns (Barber & Odean, 2000, 2013). In a similar vein, we also consider the *frequency* of depositing. While frequently depositing could simply reflect a more frequent income schedule for consumers, it may also indicate unplanned or compulsive behaviour and has been associated with problem gambling in the gambling literature (e.g., Auer & Griffiths, 2023).

In addition, we consider whether consumers have made 'night trades,' a trade between 11pm and 6am. Previous surveys have found that problem gamblers – as assessed using the PGSI - place proportionally more bets late at night (GambleAware, 2017), we have reasoned that the same could be true for investors.

We also consider same-day deposit and withdrawal. Catania and Griffiths (2022) cite cancelling withdrawals in order to re-invest the money in gambling as potentially indicative of a 'loss of control', an aborted effort to control or cut back on gambling. Analogously, withdrawing money from an investment platform before shortly re-depositing (or indeed depositing and then shortly withdrawing) may be indicative of short-term thinking and behaviour.

Catania and Griffiths (2022) also looked at 'bailout – relying on others to relieve desperate financial situations caused by gambling' – or borrowing money to gamble. We do not directly attribute specific debt to funding trading but instead take the more conservative approach of using our CRA data to flag an investor if they are in 90 days of arrears while simultaneously having positions opened on the trading app (outside of SIPPs).

Finally, we take a measure – diversification - with no immediate corollary in the gambling space. We flag if an investor is wholly invested in one non-fund asset. Funds are often diversified across one or more assets – hence we have not flagged investors who are wholly invested in one fund. We have calculated this metric by considering an investor's portfolios across all of the firms in our sample. We note that for some investors we will not see all their investments – because our data does not cover all investment firms. So, this may make an investor's total portfolio look less diversified than it would otherwise if we could see all their investments. A lack of diversification has costs for investors, exposing them to more volatile portfolios than may be appropriate (Calvet et al., 2007; Bhamra & Uppal, 2019, FCA, 2023e).

For each measure, we chose to define a threshold (as set out in Table 11) that if a consumer exceeded, they would be flagged for potentially problematic engagement. Choosing the levels of these thresholds is necessarily a judgement call. To inform our decisions, we consulted an academic expert in the field of gambling and problem gambling, Mark D. Griffiths.

Under this framework, meeting the thresholds for three to four metrics was considered 'moderately problematic engagement' and meeting the thresholds for five or more metrics was considered 'highly problematic engagement.' For the purposes of our analysis, we also separated those showing 'no problematic engagement,' meeting no thresholds, and 'low problematic engagement,' meeting the thresholds for one or two metrics.

Drawbacks and limitations

The index we propose necessarily has drawbacks. We note that individual trading app firms may not be able to check every metric that we have used in our index. Notably, due to the fact that they may not regularly (or at all) collect CRA data on customers - to assess distress or arrears. Firms, generally, will also be unable to see whether a consumer invests with another firm, let alone exactly what their full portfolio looks like.

In some instances, we would have liked to include – but ultimately had to exclude - metrics which not all firms collected or could provide us. For example, metrics which captured the time spent on platform or the number and frequency of sessions. Similarly, the use of significant leverage or a concentration of portfolios in high-risk investments (such as cryptoassets and CFDs) – especially where consumers have indicated a lower risk preference during the onboarding journey - were also metrics we wished to consider. However, because we wanted to keep the index comparable across different DEP groups (not all of which allow investment in high-risk products), we excluded these metrics. In the paper we look at all these metrics separately for the firms for which we do have data.

Ultimately, we think that this approach to identifying potentially problematic engagement on trading apps could be improved and extended with further research and testing. This may include research into the factors that predict problem-gambling-related exclusion from trading apps analogous to the approaches taken in online gambling research, summarised above (e.g., Ukhov et al., 2021; Finkenwirth et al., 2021).

12 Endeavour Square, London E20 1JN
Telephone: +44 (0)20 7066 1000 Website: www.fca.org.uk