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ORIGINAL ARTICLE

When Vegas Comes to Wall Street: Associations Between Stock Price Volatility and Trading Frequency Amongst Gamblers

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Abstract
Both gambling and trading involve risk-taking in exchange for potential financial gains. In particular, speculative high-risk high-frequency trading closely resembles disordered gambling behaviour by attracting the same individuals who tend to be overconfident, sensation-seekers, and attracted to quick large potential payoffs. We build on these studies via an incentivised experiment, in which we examine how manipulated levels of market volatility affected trading frequency. Gamblers (N=604) were screened based on the existence of household investments and recruited across the four categories of the Problem Gambling Severity Index. The volatility of stocks was manipulated between-participants (high vs. low). Participants traded fictitious stocks and were provided bonuses based on the results of their trading activity (M=US$4.77, range=[0, 16.99]). Participants traded more often in the high-volatility market, and this finding remained robust after controlling for financial literacy, overconfidence, age, and gender. Many investors trade more frequently than personal finance guides advise, and these results suggest that individuals are more likely to commit this error in more volatile markets. Exploratory analyses suggest that the effect of the volatility manipulation was strongest amongst gamblers who were at low-risk of experiencing gambling harms. As they might be otherwise considered low-risk, these individuals could be overlooked by protective gambling interventions yet nonetheless suffer unmitigated financial harms due to unchecked excessive trading.

Keywords Investing · Personal finance · Disordered gambling · Behavioural finance

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Gambling is a common activity, with around 50% of adults gambling every year in large Western countries where it is legal to do so (Calado and Griffiths 2016), and generating substantial profits for the gambling industry, equal to US$385 billion worldwide in 2016 alone (The Economist 2017). While most gamblers do not appear to suffer harm as a result, between 0.1% and 3.4% of the population of European countries meet the criteria for disordered gambling (Calado and Griffiths 2016). Furthermore, gambling researchers increasingly recognise that harm can occur even for people who score below the threshold for disordered gambling (Browne et al. 2016; Livingstone and Rintoul 2020). This has caused policy makers to treat gambling as a public health issue and led to increasing research efforts to better understand the population's risk of experiencing gambling-related harm (Adams and Rossen 2012; Regan et al. 2022; Wardle et al. 2019). This includes the increased risk of incurring harm in domains outside of gambling, such as suffering from substance-based addictions (Dowling et al. 2017).

This research focuses on examining an important potential risk associated with gambling: personal investments (Arthur and Delfabbro 2015; Arthur et al. 2016; Mosenhauer et al. 2021; Williams et al. 2023). Investing is also a common and growing activity (Aramonte and Avalos 2021), with the popularity of personal investing having doubled in a decade (McCabe 2021). While investing and gambling both involve a voluntary exposure to risk (Neal et al. 2005) the outcomes are expected to be substantially different: gambling largely leads to financial losses, while investors might reasonably expect to make money over time (Markham et al. 2016; Muggleton et al. 2021). But this is not universally true, since speculative trading, such as high-frequency trading[1] (Ortmann et al. 2020) and high-risk investments (Frino et al. 2019; Kumar 2009), often result in losses, with a pattern of returns not dissimilar to gambling (Newall & Weiss-Cohen 2022). In short, some investment products may pose risks similar to gambling.

Similar people engage in both gambling and speculative trading (Arthur et al. 2016; Philander 2023). Traders and gamblers share many cognitive similarities: overconfidence in their own skills, biased memory recall of past events (confirmation bias), and illusion of control over outcomes (Arthur and Delfabbro 2017). The two activities also share the same motivations: both gamblers and traders chase fun and excitement, are sensation and risk seekers, and are attracted by activities with payoffs skewed towards large (albeit rare) financial gains (Dorn and Sengmueller 2009; Dorn et al. 2015; Grinblatt and Keloharju 2009; Tabri et al. 2022). This conceptual overlap between gambling and speculative trading suggests a substitution effect between them, as documented in prior research (Chiah et al. 2022; Dorn et al. 2015; Orujov 2023). Lopez-Gonzalez and Griffiths (2018) described how English Premier League football teams have established partnership and sponsorship deals with both sports betting and financial trading companies, exploiting the similarities and convergences between the two activities and their target audience.

Classic personal investment guides recommend a "buy-and-hold" approach which, by minimising investment and trading costs over decades, can provide the average personal investor with good chances of a comfortable retirement (Malkiel 1999). This is in line with research findings in behavioural finance that show that more frequent trading is associated with worse returns, due to the significant costs incurred from excessive trading (Barber and

[1] In the case of our current study, when we refer to high-frequency trading, this is where an individual is trading with greater frequency, often in the same day in fast succession, as opposed to algorithmic high-frequency trading where professional traders in the market use computers to execute a large number of trades in a fraction of a second.

Odean 2000). This is especially true for day trading (high-frequency buying and selling several stocks on the same day), where it has been suggested that only 5% of day traders earn money in the long term (Barber et al. 2020; Jordan and Diltz 2003), a rate of profitability which is closer to gambling than traditional investing.

Frequent stock trading bears another similarity with characteristic features of disordered gambling: high-frequency betting or short intervals between wagering and payout ("continuous betting"), such as electronic gambling machines, are strongly associated with harm (Allami et al. 2021). Stock trading frequency has been positively associated with rates of disordered gambling severity (Mosenhauer et al. 2021), in particular short-term high-frequency day trading (Arthur and Delfabbro 2017), and gamblers at the highest-risk group on the PGSI scale are more vulnerable to harm due to excessive trading. Individuals who report having fun trading trade twice as much as their peers (Dorn and Sengmueller 2009), a behavioural pattern often seen with highest-risk gamblers. Arthur et al. (2016) suggested that these harmful structural features were not easily accessible to investors and traders in 2016, and therefore "problem investing" was extremely rare. However, with the subsequent development of mobile trading apps, which are now ubiquitous, frequent continuous trading has been made very accessible (Angel 2021; Ortmann et al. 2020), and is now common amongst retail traders (Stewart 2020). In fact, many trading platforms exploit behavioural patterns known to attract gamblers, such as frequent notifications and bonuses for volume users (Newall & Weiss-Cohen 2022). As a result, new mobile trading platforms see significantly higher turnover than older more established trading platforms (Barber et al. 2022).

How much risk investors take is another important attribute to consider in the "gamblification" of trading. Price volatility is often used as a proxy for risk in finance, either in terms of an investment's standalone volatility (Markowitz 1952) or its covariance with some wider basket of investments (Sharpe 1964). Price volatility is often measured as the standard deviation of changes in prices: higher price volatility (higher standard deviation) translates into less certain prices over time, with larger swings in prices both up and down, in other words, higher risks (i.e. higher chance of larger wins, but also of larger losses). Some would argue that only complex high-risk products, such as derivatives, have the highest potential risk and the lowest chance of allowing personal investors to make long-term profits (Chague et al. 2019), due to the excessively high volatility. But risk also varies across more common individual stocks, with the highest-risk "lottery" stocks (so called because they offer high price volatility, resulting in very small odds of large wins) being amongst the riskiest and least likely stocks to provide investors with long-term profits (Frino et al. 2019; Kumar 2009). Risk-taking is a key personality trait amongst gamblers (Wong and Carducci 1991), and as a result, investments in volatile stocks and other high-risk and high-complexity securities have also been associated with disordered gambling severity (Abreu and Mendes 2018; Arthur and Delfabbro 2015; Williams et al. 2023; Philander 2023). The association is likely to be strongest with high-volatility stocks because disordered gamblers are especially attracted to (small) chances of earning big wins (Kyonka and Schutte 2018; Ring et al. 2018). The link between gambling and trading of cryptocurrencies, another speculative high-risk type of investment, has also been established (Delfabbro et al. 2021). The potential impact of market volatility on trading frequency amongst gamblers as a way of increasing risk and excitement is therefore the focus of our study.

Given these overlapping patterns of risky behaviour across gambling and investing, we designed an incentivised online experiment to better understand the drivers of trading frequency amongst gamblers. This methodology was chosen to advance the existing literature, which often uses either historical (Frino et al. 2019; Kumar 2009) or self-reported data

(Arthur et al. 2016), making it difficult to identify the true underlying drivers of behaviour. For example, it has been shown that disordered gambling symptom severity is correlated with both self-reported trading frequency (Mosenhauer et al. 2021) and self-reported selection of high-risk investments (Arthur and Delfabbro 2015; Williams et al. 2023). However, findings using this methodology could be susceptible to confounding effects of participants' memory biases, as gamblers tend to better remember gains and forget losses (Braverman et al. 2014).

By contrast, our pre-registered experiment allowed participants, all identified as active gamblers, to buy and sell stocks in a simulated stock market, where we could objectively measure simulated stock trading frequency and test whether it is associated with disordered gambling symptomology (H1), given the similarities in motivation, behaviour, and personality traits between gambling and trading. In addition, we manipulated market volatility between-participants, to test whether gamblers would make the costly choice to trade more frequently in more volatile markets (H2), as the structural characteristics of riskier markets more closely approximate that of gambling and appeal to the risk-taking and sensation-seeking personality of gamblers. Although public health researchers stress that gambling-related harm can occur across different types of gamblers (Browne et al. 2016; Livingstone and Rintoul 2020), disordered gamblers are often the most at-risk (Markham et al. 2016), so we explored whether any interaction effects would occur between manipulated volatility levels and disordered gambling symptomology (H3).

Finally, since many of these hypothesised relationships involve observed and not manipulated variables, we also tested for any observed credible (akin to "significant" in frequentist approaches to statistical inference) effects across these hypotheses to see if they would remain after controlling for other plausible drivers of investment behaviour (H4). Specifically, these other drivers were financial literacy, overconfidence, age, and gender. Past research has observed that individuals with higher financial literacy trade less often, identifying a negative correlation between financial literacy and portfolio turnover (Firth et al. 2023; Mosenhauer et al. 2021). This can be explained as due to less sophisticated investors being more prone to futilely chasing past performance, frequently buying stocks that have displayed recent short-term gains, while more sophisticated investors understand the importance of a buy-and-hold strategy for long-term profits (Weiss-Cohen et al. 2022). Individuals with higher financial literacy also better understand the importance of minimising recurring costs associated with investments, which can quickly accumulate with frequent trading (Newall and Parker 2019). In contrast, Graham et al. (2009) find the opposite effect, that investors with higher financial literacy feel more knowledgeable, skilful, and confident, and therefore trade more often. Confident investors trade more often because they believe that they are more knowledgeable about the value of a stock than they actually are (Odean 1998); because they update their beliefs about future returns more easily and more strongly when considering new information (Hoffmann and Post 2016); and because they recall their past trading performance as better than it actually was (Walters and Fernbach 2021). Ultimately these sources of unwarranted confidence lead investors to select substantially riskier portfolios (Nosic and Weber 2010). Overconfidence is also one of the mechanisms why men trade more frequently than women (Barber and Odean 2001), in addition to males being more prone to sensation-seeking and risk-taking behaviours, such as trading and gambling (Grinblatt and Keloharju 2009), and males enjoying dealing with investments more than females (Dorn and Sengmueller 2009). A study by Grall-Bronnec et al. (2017) found that all excessive traders interviewed by them in a cohort of outpatients seeking treatment were male and high sensation-seekers. However, Mosenhauer et al. (2021) observed the opposite gender effect, with females trading more often and displaying higher overconfidence. Young individuals trade more often (Dorn and Sengmueller 2009), as they can afford to take more investment risk than older individuals with more responsibility and who are closer to retirement (Barber and Odean 2001). Young individuals might also be more acclimated to the fast pace of online and mobile trading platforms that induce frequent trading (Barber & Odean 2002). Similar correlations with gender and age have been observed in disordered gambling (Allami et al. 2021).

Our pre-registered hypotheses were:

- H1. Participants with higher scores on the Problem Gambling Severity Index (PGSI) will make more trades than those with lower scores.
- H2. Participants will make more trades as the volatility of returns increase.
- H3. There will be an interaction effect between PGSI scores and the volatility of returns.
- H4. That any credible effects from hypotheses (1–3) will persist in models adding financial literacy, overconfidence, age and gender as controls.

Methods

The pre-registered experiment consisted of two stages and participants were recruited online using Prolific (https://www.prolific.co/). In Stage 1, a questionnaire was used to identify participants who had (a) gambled in the past 12 months and (b) ever made any investments in financial markets (e.g. stocks, bonds, or funds). Only participants with experience in both gambling and investments were allowed to participate in Stage 2, which involved the main trading task. A flowchart of the recruitment process and inclusion criteria across both stages can be seen in Fig. 1. The experimental materials, data, supplement with all analyses, and pre-registration can be found online at https://osf.io/9t37g.

Stage 1

Participants

Using Prolific's internal filtering questions, we selected only users located in the USA who also responded "yes" to the investment question "Have you ever made investments (either personal or through your employment) in the common stock or shares of a company?" and did not respond "none of the above" or "not applicable / rather not say" to the gambling question "What types of online gambling / casino games have you played?" The answers to the latter were combinations of baccarat, blackjack, bingo, craps, lottery, pachinko, poker, race and sports book, roulette, slots, video poker, and video sports betting. We started Stage 1 by collecting the responses of 2184 participants using these filters.

As stated on our pre-registration, because we did not reach the targeted sample size for Stage 1 (N=3000) within 5 days, we removed the gambling filter and collected an additional 954 Stage 1 responses from users who were located in the USA and had previous investments, regardless of how or whether they responded to the online gambling filtering question. The removal of the gambling filter did not influence our targeted participant pool of gamblers and investors as our questionnaire asked all participants to confirm that (a)

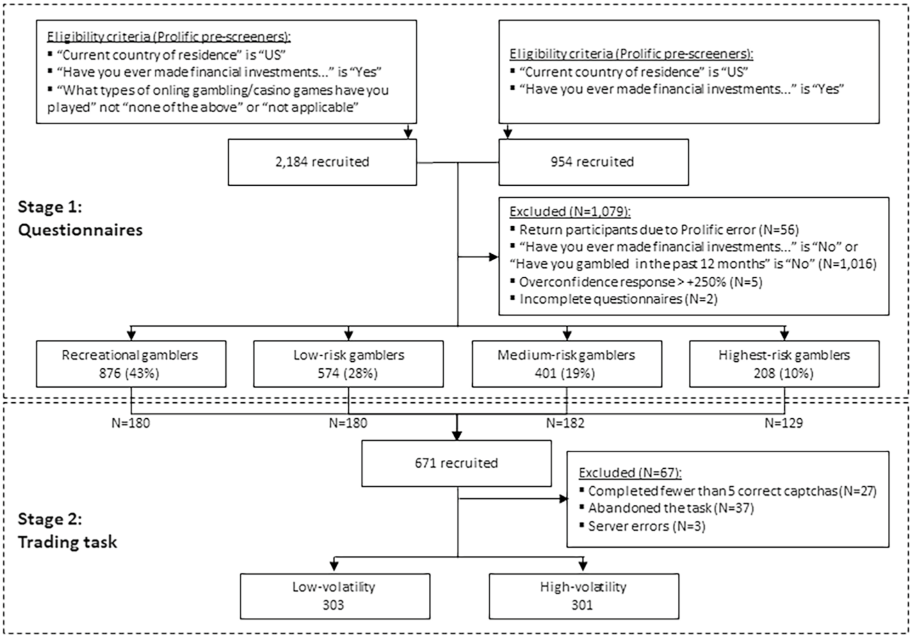

Fig. 1 Flowchart of participant recruitment across Stages 1 and 2. All figures exclude one participant who asked for their data to be removed

they had gambled in the past 12 months, and (b) they made investments in financial markets (e.g. stocks, bonds, or funds).[2]

A total of N=3138 participants were collected in Stage 1. Participants were directed to Qualtrics, where they completed a questionnaire with two sections. Participants were paid US$0.90 and took 5.8 minutes on average to complete the Stage 1 questionnaire.

Gambling Questionnaire

We asked all Stage 1 participants if they had gambled in the last 12 months, in-person or online. Participants who answered "yes" to the gambling question were asked to complete the 9-question Problem Gambling Severity Index questionnaire (PGSI: Ferris & Wynne 2001), the current gold standard measure in the field (Miller et al. 2013). Participants who answered "no" were excluded. PGSI scores correlate very highly with other measures of disordered gambling, such as gambling frequency (Howe et al. 2019), time spent gambling (Rockloff 2012), and gambling losses (Markham et al. 2016). PGSI scores had high internal reliability, with a Cronbach's alpha of 0.913.

[2] Note that Prolific does not require users to answer filtering questions. By removing the gambling filter we expanded the available pool of participants who could start Stage 1 and 57% of the additional 954 respondents reported being active gamblers via our questionnaire.

Investment Questionnaire

We asked all Stage 1 participants if they had ever made financial investments in stocks, bonds, funds, or derivatives. Participants who answered “yes” to the investment question were asked to complete the 13-question Financial Literacy questionnaire from Fernandes et al. (2014).[3] Participants who answered “no” were excluded. This financial literacy questionnaire mostly measures investment knowledge, covering topics such as bonds, stocks, diversification, and mutual funds, but also includes questions on money basics and borrowing, such as inflation and interest rates.

Participants were also asked an investment performance question, to check their level of confidence on their own investment skills: “Consider your investments for the next 12 months, and estimate by how many percentage points you will outperform or underperform the general market return (for example, the S&P 500).” Higher answers to this question indicate that the participant is more confident of their investment capabilities, as they believe they will be able to outperform the general market. This measure of financial overconfidence was taken from previous work suggesting that investors who overestimate their actual returns are likely to have outsized expectations of their expected investment returns going forwards (Walters and Fernbach 2021). We used the raw percentage reported by the participant, which could be any positive or negative percentage value. Participants who responded with a percentage higher than +250% or lower than −250% were excluded, a pre-registered exclusion criteria also used by Walters and Fernbach (2021).

Stage 2

Participants

Out of the 3138 datasets collected for Stage 1, we excluded 1016 participants who responded “no” to either the investment or gambling question. We also excluded two participants who provided incomplete datasets, 56 repeat datasets from 28 participants (due to a temporary mistake by Prolific that allowed returning participants), and five participants who provided an answer to the overconfidence question higher than the pre-registered threshold of +250% (no participant answered below −250%, the opposite pre-registered threshold). We used Prolific’s “allow-list” facility, so that only those 2059 participants who had successfully completed Stage 1 without being excluded were allowed to see the listing for Stage 2 in Prolific’s website and participate in the experiment.

Problem gambling severity is highly skewed in the population of gamblers, with very few individuals in the highest-risk category (PGSI = 8+), as confirmed by analysis of Stage 1 data (Recreational/no-risk gamblers: 43%, low-risk gamblers: 28%, medium-risk gamblers: 19%, highest-risk gamblers: 10%). The low representation of those in the highest-risk category in experimental data makes it more difficult to reliably analyse their behavioural patterns. We fixed this data problem by allowing 1/4 (N=150) of the total sample size target (N=600) to come from each of the four categories of the PGSI for Stage

[3] Since their questionnaire was initially proposed, the correct answer to Question 8 has changed due to new legislation. We updated the question to reflect the legislation at the time of data collection in 2022: after the age of 72 (and not $70\frac{1}{2}$ as originally worded) individuals must withdraw at least some money from their 401(k) or IRA (Commito 2022).

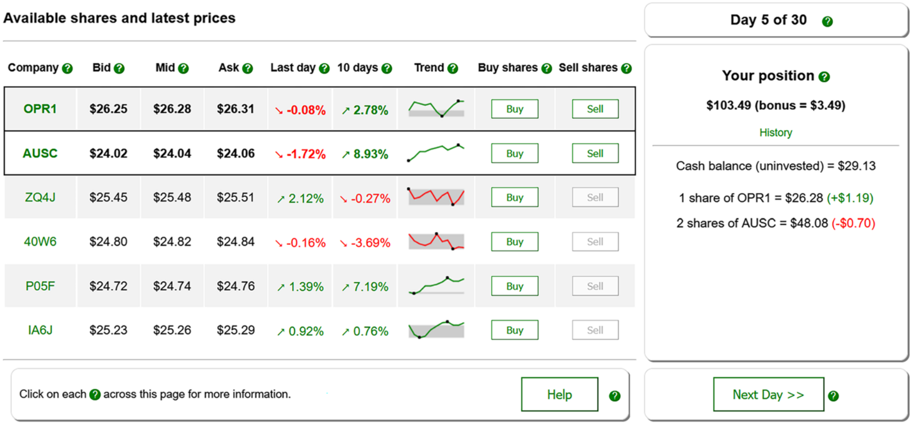

Fig. 2 Stage 2 screenshot on Day 5, showing participant owning shares in two different stocks

2. As pre-registered, because we did not reach our target after 5 days in the highest PGSI category ("highest-risk gamblers," which is the smallest category), we increased the target sample size of the remaining three categories to finish data collection.

Our target of N=600 was for participants who successfully completed Stage 2. Because we knew that some participants would not pass the initial captcha real-effort task, and also to compensate for any data losses, we allowed N=671 participants to start Stage 2.[4] Participants were paid a fixed fee of US$2.00 for their participation, plus a bonus depending on the performance of their trades (M=US$4.77, range = [0, 16.99]), and took an average of 14 minutes to complete the Stage 2 trading task. Participants received an average total compensation (fixed + bonus) equivalent to US$29/hour.

Trading Task

During Stage 2, participants traded stocks on a simulated stock exchange. Participants were first presented with a captcha typing task, an example of a "real-effort" task from behavioural economics (Erkal et al. 2011), designed so that experimental participants feel a greater sense of ownership over experimental funds given to them as an endowment, so as to better approximate trading with one's own money (Newall et al., 2022a, b, c, 2023). There were 10 captchas to be typed, randomly chosen from a full-list of 20 captchas generated in Python. Twenty-seven participants who typed fewer than 5/10 correct captcha codes were paid the fixed participation fee but did not proceed to the stock trading part of the experiment and instead their task was terminated, a pre-registered threshold. The real-effort task therefore served a secondary purpose of a check of attentiveness, which prior research using crowdsourced participants have been criticised for lacking (Pickering and Blaszczynski 2021). Thirty-seven participants abandoned the task without finishing, and three responses were excluded due to server errors. A final dataset of N=604 was analysed. Of those, 392 were male. The average age was 38.7 years (SD = 12.4).

[4] One participant asked for their data to be removed and is not included in any of these figures.

Participants who correctly typed 5/10 or more captchas were presented with the stock trading task, a screenshot of which is shown in Fig. 2. Participants were given a starting loan of US$100, plus an additional US$3 bonus endowment as a reward for successfully completing the captchas task (therefore they started the task with a balance of US$103), which they could use to buy stocks. Participants were told that any balance above US$100 at the end of the task would be paid as an additional bonus (i.e. if they ended the task with US$106 they earned a US$6 bonus). The loan of US$100 allowed for larger absolute price movements while maintaining a realistic trend of 0.1% per day.[5] As a comparison, the mean return of individual stocks of the S&P 500 index for the preceding ten-year period was 0.08% per day, based on the 507 stocks constituents, as of February 2022.

The stock trading platform was designed to be a realistic, yet necessarily simplified, trading platform. Participants could buy and sell six fictitious stocks. Participants were told that they did not have to trade, and in fact, 34 participants (6%) did not trade at all. Those who opted to trade could buy one or more share of each stock, or keep part of their balance uninvested. Stocks were given randomly generated fictitious four-letter codes, similar to actual stock tickers format-wise, but unrelated to any real-world stocks. Initial prices were generated randomly using a uniform distribution between $24 and $25.4. This range was selected so that participants could buy up to four shares (different or the same) with their initial endowment. Participants were randomly allocated to one of the two experimental conditions (low volatility, N=303, or high volatility, N=301).

The stock trading platform was programmed to last 30 simulated days. Daily returns were generated independently for each stock for each day, using a normal random number generator implemented using the Marsaglia polar method from two independent JavaScript Math.random outputs, with a volatility of either 0.5% of 1.5% per day (depending on the experimental condition, low or high, respectively), and a fixed trend (mean) of 0.1% per day. The trend and volatilities were used based on realistic returns for S&P500 stocks for the last 10 years. The 0.1% daily trend ensured that the price of all stocks would increase by 3.1% during the task. We guaranteed this by normalising the randomly generated returns if they were above or below the target. Therefore, all individual stocks were guaranteed to go up by 3.1% during the full 30-day period, but with different volatility and unpredictable movements each day.

To increase external validity, all the fictitious stocks had two prices, a *bid* price and an *ask* price, with a bid-ask spread of 0.2%, calculated from the midpoint (0.1% each way). When participants wanted to buy a stock, they paid the higher ask price. When they wanted to sell stocks, they received the lower bid price. The portfolio valuation shown on screen at all times used the *mid* (average) between bid and ask. When ending the task, the balance used to calculate the bonus was based on the mid price.

If a participant used all their initial endowment of US$103 to buy four stocks in the first day and held that position for the full 30 days, without making any additional trades, they were guaranteed to increase their balance by 3.1%, ending the task with a balance of US$106 equivalent to a US$6 bonus (after taking into account the 0.1% mid-ask spread). Because of bid-ask spreads, a participant who traded more often would, on average, earn a lower average bonus. Because of random price volatility, a participant who traded more often also introduced more volatility to their portfolio, with no additional expected reward, as the daily trend was the same for all stocks in both experimental conditions.

[5] Lower starting amounts without a loan would translate into very small absolute price movements and lower final bonuses.

Table 1 Median of the posterior distribution for each parameter in Model M1

Parameter	Median	95% CrI (HDI)	pd	R-hat	ESS
(Intercept)	2.421	[2.325, 2.520]	100%	1.000	37,570
volatility=high	0.159	[0.021, 0.296]	98.8%	1.000	35,701
pgsi (centred)	0.015	[−0.005, 0.036]	93.0%	1.000	26,827
volatility=high : pgsi (c)	−0.008	[−0.036, 0.021]	70.5%	1.000	26,476

PGSI was centred. 95% CrI is the highest-density Credible Interval around the median. Probability of direction (pd) is the proportion of the posterior distribution that is of the median's sign, and can be interpreted as the probability that a parameter is positive or negative. R-hat is Brooks-Gelman-Rubin scale reduction factor. ESS is the Effective sample size, indicating the number of independent samples used to produce the estimates

While the median final balance was very similar in both conditions (low: Md=$104.65, high: Md=$104.62), the standard deviation of final balances was higher in the high condition (low: SD=$1.39, high: SD=$3.38). Both the largest and lowest final balances across all participants were in the high condition ($116.99 and $92.68 respectively) while the final balances in the low condition were considerably less extreme (between $110.51 and $101.53). The higher volatility of prices in the high experimental condition resulted in participants experiencing larger price swings, and provided the opportunity for large gains, but also for losing the endowment (bankruptcy), similar to gambling outcomes — which were not observed in the low experimental condition. In the high condition 19 participants ended with balances above $110 and 18 participants ended with balances below $100 (and therefore earned no bonus) while in the low condition only one participant ended with a balance above $110 and no participant ended with a balance below $100.

Ethics

The study received ethical approval from the University of Leeds School of Business, Environment and Social Services Committee (LTLUBS-374). All participants were informed about the study's contents, and all provided informed consent to participate.

Analyses and Results

The dependent variable was *trade count*: the total number of trades made by each participant. The distribution of the dependent variable most closely approximated a negative binomial distribution. Therefore, we fitted negative binomial general linear regression models with a log link function using R 4.3.0 (R Core Team 2023). We used a Bayesian framework estimated using MCMC sampling with 4 chains of 10,000 iterations and a warmup of 2000, with non-informative priors. Convergence and stability of the Bayesian sampling have been assessed using R-hat, which were all below 1.01 (Vehtari et al. 2019), and Effective Sample Size (ESS), which were all greater than 1000 (Bürkner 2017). These numbers suggest that the models converged successfully and were stable. As preregistered, inferences were based on the 95% Credible Intervals (Highest Density Interval) excluding zero, and strength of evidence for the presence of an effect were reported using the probability of direction (pd).

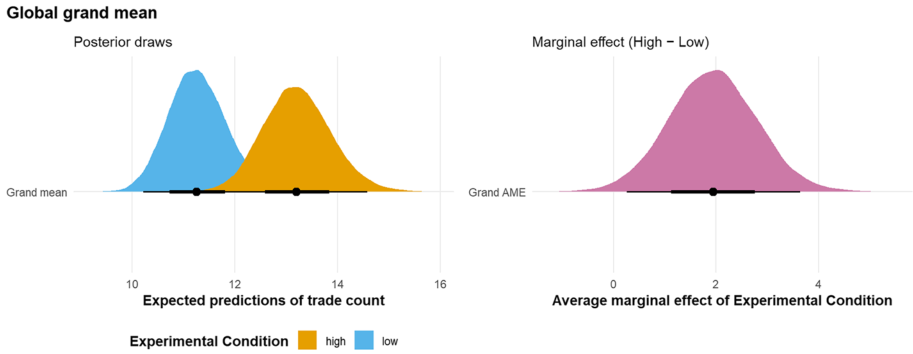

Fig. 3 Difference in estimated trade count between low and high volatility, at the average PGSI score

The first model fitted (M1) was used to test for hypotheses H1-H3 and had two predictors, volatility condition (Low or High), PGSI scores (centred), and their interaction (Table 1). We did not observe evidence for a substantial association between PGSI and trade count, meaning that H1 was not supported by the data. As is indicated by Table 1, not only does the credible interval of 95% probable values include 0 as an effect, the range of probable values is narrow, suggesting only a small positive relationship (pd = 93%).

We observe credible evidence for a main effect of the volatility manipulation, which supports H2. Participants in the high-volatility condition made on average around 2 (17%) more trades than participants in the low-volatility condition (High = 13.20, Low = 11.26, Difference = 1.94, 95% CrI = [0.25, 3.64], pd=98.8%, ROPE=10.9%). There is 98.8% probability that the effect is *positive*, and only 10.9% probability it is *negligible* in size (we used a Region of Practical Equivalence, or ROPE, of ±0.08, equivalent to one trade difference, to identify a minimum effect size of interest). Increasing the volatility of prices, and allowing for larger price swings, led to a larger number of trades made by participants overall.

According to the regression coefficients in Table 1, there was no credible evidence for an interaction between PGSI and the volatility manipulation, meaning that H3 was not supported by this pre-registered model. However, an exploratory analysis in the next section will investigate this interaction in more detail and provide post hoc evidence to support H3.

Overall, model M1 provides evidence that *all* participants (who were all gamblers) had a tendency to trade more in the experimental condition with higher price volatility (Fig. 3).

In following the pre-registration, we proceeded to investigate the robustness of the significant effect of the volatility manipulation on trade count, by adding measures of individual differences. As planned, this proceeded in two hierarchical steps starting from model M1: first, we included overconfidence (as measured by the single question on one's own future investment performance from Walters and Fernbach 2021) and financial literacy (as measured by the questionnaire from Fernandes et al. 2014) as model M2, then we included age and gender as model M3.

Table 2 provides the regression coefficients with the new covariates. None of the additional covariates showed credible evidence for an influence on trade count (all new 95%

Table 2 Model coefficients for M2 and M3. Median of the posterior distribution for each parameter

	Model M2			Model M3		
Parameter	Median	95% CrI	pd	Median	95% CrI	pd
(Intercept)	2.421	[2.325, 2.521]	100%	2.375	[2.233, 2.251]	100%
volatility=high	0.157	[0.017, 0.296]	98.6%	0.146	[0.007, 0.285]	98.0%
pgsi (centred)	0.014	[−0.006, 0.035]	91.4%	0.013	[−0.008, 0.034]	88.4%
fin. lit. (centre)	0.002	[−0.026, 0.030]	56.1%	−0.002	[−0.033, 0.029]	55.3%
overconfid.(c)	−0.289	[−0.736, 0.171]	89.4%	−0.307	[−0.735, 0.136]	91.1%
sex=male				0.084	[−0.078, 0.242]	84.6%
age (centred)				−0.002	[−0.009, 0.004]	77.9%
vol=high:pgsi(c)	−0.006	[−0.034, 0.023]	65.8%	−0.006	[−0.035, 0.022]	66.9%

PGSI, overconfidence, financial literacy, and age were centred. 95% highest-density Credible Interval around the median (HDI). Probability of direction (pd) is the proportion of the posterior distribution that is of the median's sign, and can be interpreted as the probability that a parameter is positive or negative

CrIs included zero). Crucially, the two 95% CrI for the effect of volatility on trade count (for models M2 and M3) do not include zero. These results provide evidence that the effect of volatility (H2) observed in M1 remains credible in M2 and M3, supporting H4: any effects observed remained credible after the introduction of control variables.

Exploratory Analysis

While the overall average marginal effect (AME) for the interaction of PGSI and Volatility manipulation, as measured by the coefficient in Table 1, did not show a large or definitive credible effect, we conducted a post hoc exploratory analysis looking at the effect of the volatility manipulation at different levels of PGSI scores. This additional analysis should not supersede the primary pre-registered analyses, but it reveals important differences and provides nuance to the findings and to future research.

The lack of an interaction may be driven by the oversampling of the highest-risk gamblers in comparison to their true population frequency (see Stage 1). These individuals seem unaffected or more inconsistently affected by the volatility manipulation. Highest-risk gamblers may exhibit different trading behaviour from those scoring lower on PGSI. This heterogeneity of conditional variances in our model lends itself to our decision to probe the interaction in more detail, as the relationship of the moderator with the covariate does not seem consistent at all scale points.

We calculated marginal effects at representative values (MERs) for the effect of the volatility manipulation — in other words, the difference in number of trades between high- and low-volatility experimental conditions — for four different levels of PGSI. As the Bayesian framework does not necessitate dichotomous decisions nor produce problematic inferences from multiple testing, we can interrogate the data based on theoretically meaningful values (MERs), without concerns for "error inflation." Given the importance of the subject matter, we did not want to ignore patterns within the data simply due to the higher estimation uncertainty in the top-end of the scale. We used the observed average PGSI for each of the four main categories of gambling disorder (Recreational/no-risk gamblers: PGSI equal to 0, mean = 0; low-risk gamblers: PGSI equal to 1 or 2, mean = 1.35;

Table 3 Result of post hoc analysis of differences in trade count between High and Low conditions for different levels of PGSI

	Trade Count		Marginal difference High − Low			
PGSI (average score)	Low	High	Diff.	95% CrI	pd	ROPE
No-risk (0.00)	10.59	12.80	2.21	[0.13, 4.30]	98.2%	10.5%
Low-risk (1.35)	10.81	12.93	2.12	[0.25, 4.01]	98.8%	9.7%
Medium-risk (4.41)	11.33	13.24	1.91	[0.20, 3.63]	98.7%	12.7%
Highest-risk (12.50)	12.81	14.07	1.25	[−2.53, 5.02]	74.9%	34.8%

95% highest-density Credible Interval around the median (HDI). Probability of direction (pd) is the proportion of the posterior distribution that is of the median's sign and can be interpreted as the probability that a parameter is positive or negative. Region Of Practical Equivalence (ROPE) measures the probability that an effect is negligible in size, here measured against a change of ±1 trade

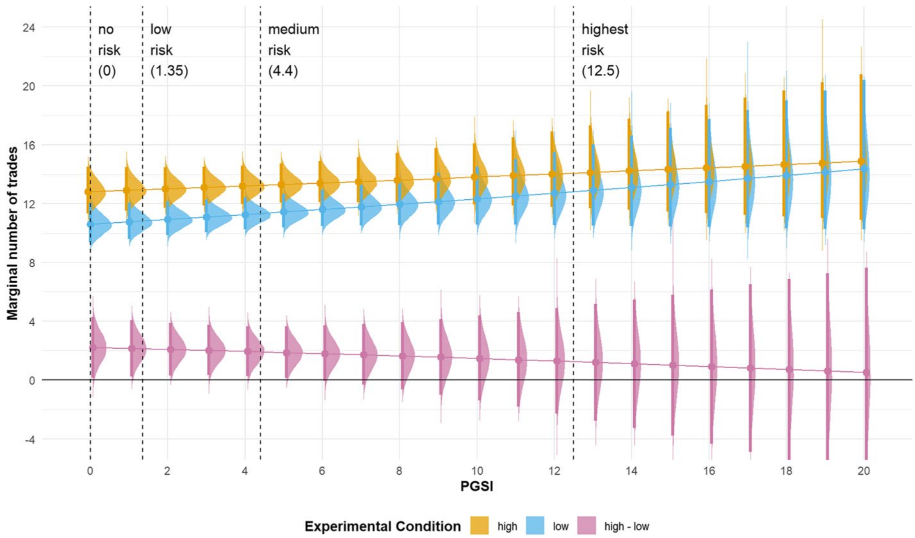

Fig. 4 Post hoc differences in estimated trade count between low and high volatility, for different levels of PGSI scores. The dashed vertical lines identify the average PGSI scores for each of the four categories. The orange and blue data show the medians for high-volatility and low-volatility experimental conditions, respectively, while the purple data is the difference between the two

medium-risk gamblers: PGSI between 3 and 7, mean = 4.41; highest-risk gamblers: PGSI between 8 and 27, mean = 12.50). The group average for highest-risk gamblers confirms the lack of participants at the higher end of PGSI: the mean is only 1/4 of the possible range of PGSI values for that category.

The results of this analysis in Table 3 show credible differences in trading frequencies between high- and low-volatilities for participants in the three lowest levels of PGSI (0, 1.35, and 4.41), but not for the highest level (12.50). From these post hoc results, we see credible evidence for a potential interaction effect between PGSI and the volatility manipulation. For participants in the lowest three PGSI categories (i.e. excluding highest-risk gamblers), there was at least a 98.2% probability that the volatility manipulation increased the number of trades, and there was a maximum of 12.7% probability that the effect was negligible in size (i.e. increased trading by fewer than one additional trade). No credible differences were observed for participants in the highest PGSI category (highest-risk gamblers).

Accordingly, one possible post hoc speculation that arises is that volatility manipulations may have an effect on trading frequency only for individuals that are not at the highest risk level for disordered gambling. This exploratory analysis indicates support for H3. Figure 4 plots these results, showing differences amongst the two experimental conditions for participants with lower PGSI scores, but not for those with higher PGSI scores.

Discussion

More people are investing today than ever before (Aramonte and Avalos 2021; Chiah and Zhong 2020). Ease of investing associated with rapidly growing mobile trading apps drives both increased trading activity by existing investors as well as new accounts being opened by first-time less sophisticated investors (Angel 2021; Ortmann et al. 2020; Ozik et al. 2021). Similar harmful trends have been observed with mobile phone gambling (Barber et al. 2022; Hing et al. 2022). Retrospective self-report studies have linked levels of disordered gambling symptomology with both stock trading frequency (Mosenhauer et al. 2021), and higher likelihood of selecting high-risk investments (Arthur and Delfabbro 2015; Williams et al. 2023). When pandemic-related lockdown restrictions halted sports matches and closed casinos and other betting houses in 2020, high-risk speculative retail trading activity increased significantly (Chiah et al. 2022; Håkansson et al. 2021; Orujov 2023). We therefore implemented an incentivised online stock trading task, where gamblers invested in simulated markets of different volatility levels, to further investigate the links between trading and gambling activity, and how trading platforms might be exploiting these links. As hypothesised, we found that participants trade more frequently in the more volatile market (H2), that this effect is potentially moderated by PGSI scores in exploratory analysis (H3), and these effects are not attributable to individual differences in financial literacy, overconfidence, age, or gender (H4).

By using a simplified market with simulated stocks with two different volatility levels, we were able to observe, within the same framework, two distinct behaviours amongst gamblers — one that was more investment-like (low volatility) with fewer trades, and one that was more gambling-like (high volatility) with more trades. Larger value swings increase the chances of making larger gains (a shot at riches) but also increase the chance of losing large amounts, which we replicated here in our high-volatility experimental condition. Because participants who ended our study with balances below US$100 did not incur financial losses, the rewards in the high condition were positively skewed towards higher values, with a cap on losses, similar to how games of chance motivate gamblers (Kumar 2009). Easy availability of high-volatility high-risk investment products in existing trading platforms might expose gamblers to an alternative way to seek similar sensations as can be found in gambling, by trading excessively, at the same time enabling trading platforms to profit from higher trading volumes (Rooney and Fitzgerald 2020; Philander 2023).

We did not observe a credible main association between disordered gambling symptomology and trading frequency (H1). Despite our best efforts to recruit participants with higher PGSI scores, because of the relatively low prevalence of at-risk individuals in the overall population, our experiment lacked participants with the highest-risk group on the PGSI scale. This increased the variance and uncertainty of the results and reduced the ability of the model to make reliable predictions for individuals with high PGSI. Nevertheless, our post hoc exploratory analysis showed tentative evidence for a credible interaction between PGSI and our volatility manipulation (H3). We present some evidence that participants in the lower end of PGSI, or those with little to no gambling risk, were the most likely to increase their trading activity when exposed to higher price volatility. While the focus of our current study was the ongoing "gamblification" of trading, and all our participants were gamblers, future studies should explore how non-gamblers engage with trading platforms, and if they also trade excessively and could be exposed to potential financial losses as a result. It is possible that comparing gamblers against non-gamblers would provide further evidence for our hypothesis comparing gambling symptomology with trading frequency (H1).

Our results show that increasing the volatility in a market, for example by providing access to riskier products, can be particularly detrimental to those who are lower-risk gamblers. Traditional approaches to minimising gambling-related harm have focused on those at the highest level of risk: disordered gamblers (Petry et al. 2017). However, the more recent public health approach recognises that harm can occur across the population of gamblers, and that it is more appropriate to try and reduce population levels of risk, for example via marketing or product restrictions (Adams and Rossen 2012; Newall et al., 2022b; Regan et al. 2022; Wardle et al. 2019). The present results are perhaps more consistent with this public health approach, as they show how being provided with high-volatility products affects in particular those who would be considered as low-risk and would not be targeted by traditional harm-reduction campaigns. Since this effect remained credible when controlling for overconfidence and financial literacy, this further suggests that individual-based interventions, such as teaching investors the basics of financial literacy, may not be effective at teaching investors to trade less frequently (Fernandes et al. 2014). For example, restrictions on the speed and ease with which online gambling products can be used is one proposed public health intervention in gambling (Newall et al., 2022b), and a similar approach could one day be considered to mitigate potential harms from online trading platforms.

These interpretations are subject to the various limitations of the present study. No experimental task can be as realistic or engaging as real-life investing is, nor offer incentives comparable to an investor's actual wins or losses. While on average participants earned US$29/hour with some participants surpassing US$100/hour, the starting balance of US$103 was relatively low in comparison with a typical mobile trading account size of US$2000 (Welch 2022). In fact, observing behavioural differences with relatively small amounts speaks to the allure of market volatility. It is not difficult to envisage that an increase in stakes would increase risk, excitement, and potential for gains, enticing participants in the higher categories of PGSI to trade more often, providing more evidence to support H1. One must also balance the ethical implications of allowing participants to trade their own funds, and the risk of financial harm in case of losses. Nevertheless, our use of a real-effort task has been shown to increase the ownership that participants feel of the money provided during the task, increasing engagement and effort (Erkal et al. 2011), with realistic patterns of behaviour when used in gambling experiments (Newall et al., 2022a, b, c, 2023). The platform used was made to look and feel as realistic as possible, given the constraints of a controlled experimental setup. Other researchers have created "trading addiction" measures, based on existing gambling screening instruments (Cox et al. 2020; Youn et al. 2016), and those measures might have stronger associations with trading frequency than PGSI. Future research could investigate allowing participants to choose in which markets they want to trade, as it is likely that highest-risk gamblers would actively prefer the excitement of high-volatility trading.

Our study adds to a growing body of knowledge of the intersection between investing and gambling, and highlights the importance of regulatory intervention to ensure that individuals are not exposed to gambling disguised as trading, for example by allowing easy access to high-volatility products such as cryptocurrencies. We show how even within the world of stock trading, which does not initially attract the same societal associations as high-risk speculative trading, gambling-like behaviour can surface via the simple introduction of more volatile stocks. In particular, individuals at the lower-risk end of the PGSI scale were the most likely to be detrimentally affected by the easy availability of such high-risk trading products. Policy makers and researchers should not ignore recreational and low-risk gamblers in their initiatives, as our research shows that these individuals are more susceptible to market manipulations, and could suffer financial harm as a result of the recent expansion in trading platforms offering easy access to high-volatility products.

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Declarations

Informed Consent All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000 (5). Informed consent was obtained from all patients for being included in the study.

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