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Nonlinear Trading-Performance Patterns Among Novice Participants in an Incentivized Trading Simulation

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Abstract

This article analyses trading-performance patterns in a stock market simulation conducted with 134 second-year students at the University of Mons (Belgium) on 11 December 2025. Participants had a virtual capital of 100,000 euros and were free to trade CAC 40 securities without any restrictions on the number or volume of transactions. An academic incentive scheme, combining a participation bonus and bonuses for the three best portfolios, created a tournament-style environment with continuous ranking feedback. This feature is considered as part of the experimental context rather than as a separately identified causal mechanism. We estimate a quadratic model linking performance to activity, measured by the number of mean-centered transactions to reduce the collinearity between the first-degree term and its square, and control exposure via the average percentage of cash in the portfolio, portfolio variability (measured as the standard deviation of portfolio value) and the average trade size. Breusch–Pagan and White tests indicate heteroscedasticity, justifying a robust inference. The results highlight a convex relationship between activity and performance: the marginal association is initially negative but becomes positive above a model-implied upper-tail level corresponding to approximately 46 transactions. This value should not be interpreted as a behavioral level or as a trading rule. The percentage of cash in the portfolio and the average trade size are negatively associated with performance, while the portfolio variability does not show a statistically significant association with performance. Overall, the results indicate heterogeneous trading patterns rather than a single activity–performance profile.

Keywords: behavioral finance; overtrading; trading simulation; performance; incentives

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1. Introduction

Behavioral finance shows that investment decisions frequently deviate from "standard" rationality, particularly when uncertainty is high and the investment time horizon is short (Shiller, 2003). In these contexts, investors may rely on heuristics and may be subject to biases, such as loss aversion and asymmetric sensitivity to gains and losses (Kahneman & Tversky, 1979) or the illusion of control, which leads to overestimating an individual's ability to influence essentially random outcomes (Langer, 1975). A central mechanism linking these biases to performance is the dynamics of overtrading: the belief that investors can better time the market encourages excessive trading and, on average, worsens performance (Odean, 1999; Barber & Odean, 2000). This logic is consistent with the idea that investors may overreact to informational signals and generate phases of overreaction in prices (Daniel et al., 1998), while overconfidence is a determinant of trading volume (Statman et al., 2006).

However, trading activity may reflect more than irrationality (Griffin et al., 2003). In environments where learning is the central component, and opportunities must be captured quickly, higher frequency may reflect a greater ability to adjust and process information, as suggested by results from experimental markets (Plott & Sunder, 1982). This ambiguity is evident in competitive incentive schemes (Chevalier & Ellison, 1997). Tournament-type compensation schemes alter trade-offs and may encourage extreme risk-taking behavior (Lazear & Rosen, 1981; Nalebuff & Stiglitz, 1983). At the same time, the literature on incentives and rankings shows that performance-seeking behavior can generate strategies to intensify activity and "reduce performance shortfalls" (Basak & Makarov, 2014), even at the cost of greater variance in results (Brown et al., 1996; Busse, 2001). In summary, over a short, competitive and incentive-driven time horizon, the effect of activity on performance cannot be assumed to be monotonic, as activity can be consistent with different trading patterns, including inefficient over-activity and more structured forms of portfolio adjustment (Foucault et al., 2016).

To provide some answers to this question, we are using data from a stock market simulation carried out with 134 second-year undergraduate students in Management Sciences at the University of Mons (Belgium), over a period of four hours, with a virtual capital of 100,000 euros and the possibility of freely trading CAC 40 securities. An incentive scheme (participation bonus and bonus for the three best portfolios) aims to stimulate engagement while creating competitive pressure that may affect trading styles (Carpenter, 2000). Empirically, we estimate a quadratic model linking performance to activity, measured by the number of transactions, mean-centered to address multicollinearity concerns and improve the stability of estimates and the identification of a turning point. We control exposure and decision implementation via the average percentage of cash in the portfolio, the standard deviation of the portfolio value and the average trade size, with reference to the theoretical framework of portfolio selection proposed by Markowitz (1952). Our empirical design does not directly measure psychological constructs such as overconfidence, attention, risk tolerance, beliefs, expectations, or learning. The behavioral-finance literature is used to motivate plausible interpretations of trading patterns, not to identify the psychological mechanisms behind individual trades. Accordingly, the empirical contribution of the paper is located at the level of trading-performance patterns among novice participants in a short, incentive-based simulation.

The research question will be formulated as follows. In a short-term, incentive-based stock market simulation, is trading intensity associated with performance, and is this relationship non-linear once exposure dimensions and average transaction size are controlled for?

The main contribution of this paper is to document heterogeneity in trading-performance patterns among novice participants operating in a short-horizon, incentive-based trading simulation. The paper shows that trading frequency, cash exposure, and trade implementation are associated with final performance in non-monotonic and context-dependent ways. This contribution is relevant for investor education and for the design of trading simulations, especially when performance feedback is made visible to inexperienced participants.

2. Theoretical Framework and Development of Working Hypotheses

To explain the performance in a short and competitive stock market simulation, we use a framework that includes behavioral finance, portfolio theory and incentive economics. Investment decisions involve balancing risk and return, cognitive biases (overconfidence, illusion of control) and adjustments related to competition (Langer, 1975; Kahneman & Tversky, 1979; Daniel et al., 1998). The literature on individual investor trading suggests that excessive trading can impair performance, while at the same time reflecting high levels of skill, which justifies the study of a non-linear relationship (Odean, 1999; Barber & Odean, 2000; Statman et al., 2006). Exposure depends on portfolio choices: high liquidity reduces access to upward movements, particularly under tournament-type incentives (Markowitz, 1952; Lazear & Rosen, 1981; Brown et al., 1996). Finally, average transaction size may signal investment concentration (Kyle, 1985), while portfolio variability may reflect both exposure and strategy instability (Sharpe, 1964; Fama & French, 1993; Odean, 1999). On this basis, we formulate four working hypotheses linking activity, exposure, transaction size, portfolio variability and performance. A distinction must be made between theoretical mechanisms and their empirical operationalization. In this study, explanatory variables are not direct behavioral measures. The number of transactions, the average percentage of cash, portfolio-value variability, and average transaction size are trading indicators. They are considered as indicators of trading style, not as direct measures of cognitive biases, preferences, beliefs, or learning processes. For this reason, the hypotheses are formulated as associations between trading indicators and performance, rather than as tests of psychological mechanisms.

2.1. Hypothesis Relating to the Level of Activity

For the level of activity, we start from a working hypothesis suggesting a convex relationship between activity and performance, as the level of activity could aggregate two opposing influences. On the one hand, the literature shows that an increase in trading frequency can degrade performance through overtrading, often linked to overconfidence and the illusion of control, which leads to a proliferation of decisions and a decline in performance (Odean, 1999; Barber & Odean, 2000; Langer, 1975). According to this perspective, an increase in the number of decisions would reflect impulsiveness rather than competence (Daniel et al., 1998; Statman et al., 2006). On the other hand, in competitive environments with a short time horizon, high activity may also be compatible with more structured adjustment, although this mechanism cannot be directly identified with the available variables (Plott & Sunder, 1982). Tournament-style incentives can further accentuate behavioral heterogeneity. Some may adopt impulsive trading, which leads to underperformance, while others may manage to take advantage of high activity, making a reversal of the trend possible (Lazear & Rosen, 1981). The diversity of trading styles, ranging from excessive activity to more disciplined activity, makes a convex relationship plausible. A quadratic coefficient can then be used to model the subsequent improvement in performance when activity becomes sufficiently high. In summary, H1 is based on the idea that at low to moderate levels of activity, trading intensity is accompanied by more errors and underperformance, while at higher levels, activity may be compatible with more structured adjustment, although the underlying mechanism cannot be directly identified with the available variables, leading to a convex relationship (Odean, 1999; Barber & Odean, 2000; Statman et al., 2006; Plott & Sunder, 1982). It should be noted that our empirical design does not include a direct measure of overconfidence, nor does it allow us to estimate mediation paths. We do not test the mechanism “overconfidence, trading and performance” as such. Instead, we test whether trading intensity is associated with performance, consistent with an overtrading channel documented in the literature.

H1. *The activity–performance relationship is convex: the first-degree coefficient is negative, and the quadratic coefficient is positive. It should be noted that if this hypothesis is supported, we will highlight a turning point. The turning point refers to the level of activity at which the estimated relationship between trading activity and performance changes direction. Below this point, carrying*

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out more transactions is associated with poorer performance, which corresponds to the logic of over-trading (errors, ineffective decisions). Above this point, higher activity is associated with better performance, conditional on the model controls. This pattern may be compatible with more structured adjustment among highly active participants, but it does not identify the underlying psychological mechanism.

2.2. Hypothesis Regarding Portfolio Composition

The second working hypothesis is based on the idea that, in the short term and in a competitive environment, holding a high proportion of cash reduces exposure to price fluctuations and therefore the ability to take advantage of upward movements, which can impair performance. Under-exposure to risky assets limits performance potential, especially when the objective is to outperform others. This intuition is consistent with mean-variance theory, where the optimal combination depends on the risk-return trade-off and where a cautious allocation can reduce the expected return (Markowitz, 1952). In a tournament environment, incentives to rank can encourage risky strategies (Lazear & Rosen, 1981; Brown et al., 1996). In addition, short-term evaluation often increases sensitivity to relative performance, which can increase the opportunity cost of holding excessive cash when the market trend is bullish. Finally, risk preference models suggest that overly cautious strategies may become suboptimal when the objective is competitive and not the maximization of long-term utility (Kahneman & Tversky, 1979). Thus, H2 predicts a negative association between the percentage of cash in the portfolio and performance in a short simulation, where the opportunity for return is highly dependent on exposure.

H2. *A high proportion of cash in the portfolio is associated with lower performance.*

2.3. Hypothesis Regarding Transaction Size

The third hypothesis concerns average transaction size. In our study, average transaction size is used as an implementation indicator rather than as a direct measure of concentration, diversification, or risk control. A higher average transaction size means that, for a given level of activity, participants committed larger amounts per transaction. Such a pattern may be compatible with more concentrated execution or less gradual portfolio adjustment, but the variable does not directly identify turnover, holding-period strategies, or the number of distinct securities held. This distinction is important because portfolio concentration and diversification are portfolio-level constructs, whereas our indicator is computed at the transaction level (Markowitz, 1952).

From a portfolio perspective, larger trades may increase exposure to specific positions when they are not offset by sufficient diversification, which can affect the risk-return profile (Markowitz, 1952). In terms of market microstructure, trade size may also be viewed as an element of order implementation, although it should not be confused with a measure of skill or trading sophistication (Kyle, 1985). However, because the indicator is computed at the transaction level, it should be interpreted cautiously. It reflects the average monetary size of trading decisions, not the complete structure of the portfolio. H3 therefore tests whether average transaction size is associated with final performance, without claiming that it measures concentration or overconfidence.

H3. *A higher average transaction size is negatively associated with performance.*

2.4. Hypothesis Regarding Portfolio Variability

Portfolio variability is measured as the standard deviation of portfolio value over the simulation. Given the short horizon, this indicator is considered a proxy for exposure instability rather than as a measure of risk management. Over a short session, portfolio fluctuations are more sensitive to short-run price changes, which may increase measurement error. In this context, portfolio variability may reflect several overlapping dimensions, including exposure, concentration, unstable portfolio adjustments, and short-term reactions that may be consistent with patterns discussed in the behavioral finance literature (Daniel et al., 1998; Odean, 1999). It is therefore included as an exploratory control reflecting differences in portfolio value instability across participants. The expected direction of its association with performance remains theoretically ambiguous (Campbell et al., 2001).

H4. *Short-horizon portfolio-value variability may be associated with performance, with no ex ante prediction regarding the sign.*

Based on these four working hypotheses, our final model is formulated as follows:

$$\widehat{RDT}_i = \hat{\alpha} + \widehat{\beta_1} Act_{c,i} + \widehat{\beta_2} Act^2_{c,i} + \widehat{\beta_3} Cash_i + \widehat{\beta_4} PV_i + \widehat{\beta_5} Vol_i + \varepsilon_i$$

where

- $\widehat{\mathrm{RDT}}_{\mathrm{i}}$: individual performance over the period (dependent variable), percentage change between the value of the portfolio at the end of the simulation and its value at the beginning.
- Act: total number of transactions.
- $\mathrm{Cash}_{\mathrm{i}}$: average percentage of cash in the portfolio.
- PV_{i}: portfolio variability.
- $\mathrm{Vol}_{\mathrm{i}}$: average transaction size.
- ε_{i}: term of error.
- $Act_{c,i} = A_i - \overline{A}$.
- $Act^2_{c,i} = \left(A_i - \overline{A}\right)^2$.

Before moving to our results, we will outline the rationale for using activity expressed as deviations from its mean rather than the total number of transactions (see Section 4). Moreover, it should be noted that a quadratic specification is essential because a monotonic model would impose a single activity effect and would therefore hide any turning point in the activity–performance relationship.

3. Data and Experimental Context

The study is based on an experiment involving 134 second-year undergraduate students in Management Sciences at the University of Mons (Belgium). All participants had completed an introductory finance course, but they had not yet completed the final exam when the simulation took place. They were at an early learning stage: core concepts had been covered, while practical market experience and knowledge consolidation remained limited. This sampling strategy defines the scope of the findings. The study is designed to document decision patterns among novice participants. Because the participants are educationally homogeneous, the results should be interpreted as evidence from a controlled novice-investor setting, with limited generalizability to experienced market participants. At the same time, this setting remains informative for understanding trading behavior among novice investors at a first stage of participation in stock-market environments, when market familiarity, trading discipline, and behavioral adjustment are still developing. This focus is also relevant because early-stage market participants are less often examined as a distinct target population in the finance literature (Huber & Kirchler, 2023; Fréchette & Schotter, 2015). Comparable simulations were previously conducted with students' samples in December 2024 and April 2025. Those studies relied on qualitative approaches based on participants' narratives rather than on a quantitative model designed to identify statistical relationships (Finet et al., 2025c; Finet et al., 2025b).

Stock-market simulations are particularly well suited to examining such incentive-driven dynamics (Finet et al., 2025a), because they combine realistic features (such as price movements and transaction costs) with controlled experimental conditions (Do & Faff, 2010; Ackert et al., 2006). They are especially appropriate for novice investors, as they make it possible to analyze "first exposure" behavioral responses in settings that remain close to actual markets. This emphasis on novices (e.g., undergraduate students) aligns with experimental design considerations: early decision episodes are often marked by heightened emotional responsiveness and limited self-regulatory capacity (Weber & Milliman, 1997). More broadly, student samples are justified when the objective is to test theoretical mechanisms under specified conditions, particularly when the processes under investigation relate to initial exposure effects (Fréchette & Schotter, 2015). Seminal contributions in experimental economics also highlight that validity depends less on demographic representativeness than on how well the sample matches the theoretical target of the study (Harrison & List, 2004). For financially and emotionally charged tasks, this reasoning is particularly relevant: students may display less calibrated confidence, stronger feedback sensitivity, and more pronounced affective reactions, offering a relatively "clean" window into how task-induced emotions influence performance before experience gradually reshapes those responses (Levitt & List, 2007).

The simulation was held on 11 December 2025, from 1:30 p.m. to 5:30 p.m. Participants managed a virtual portfolio of €100,000 and were allowed to trade only CAC 40 constituents. Short selling was not permitted, and no limit orders were available; this choice was intended to preserve a homogeneous framework for the transactions carried out. The trading session was conducted on the ABC Bourse platform, using a dedicated simulation environment. Rankings were updated continuously throughout the session. To ensure ecologically valid decision freedom, participants received no instructions regarding how many trades to execute, when to trade, or what trade sizes to choose. Accordingly, they were free to pursue either highly active or more conservative trading styles. To promote participation, we implemented a tournament-type incentive scheme: the top-performing portfolio received a 2-point exam bonus, the second-ranked portfolio 1.5 points, and the third-ranked portfolio 1 point. In addition, every participant received 0.5 bonus points for taking part. The incentive scheme and ranking feedback are not treated as separately identified mechanisms. Since all participants were exposed to the same institutional environment, the design does not allow us to estimate the causal effect of tournament incentives. These features define the context in which the trading-performance patterns emerged. A transaction cost of 0.2% was implemented so that performance would reflect the financial consequences of trading intensity. Over the trading window, the CAC 40 index increased by approximately 0.30%, rising from 8061.40 points at 1:30 p.m. to 8085.76 points at 5:30 p.m. The session took place in a slightly rising market, which is important for interpreting the role of cash holdings and portfolio exposure. Following experimental economics reporting standards, the complete instructions and a detailed description of the ABC Bourse protocol are reproduced in Appendix A.

4. Empirical Strategy and Results

We first considered a specification in which activity is captured by the total number of transactions (and its square) without mean-centering for activity, yielding the following model. This formulation, however, raises multicollinearity concerns between the linear and quadratic terms, which can increase standard errors and complicate the interpretation of the non-linear effect.

$$\widehat{RDT}_i = \hat{\alpha} + \widehat{\beta_1}Act_i + \widehat{\beta_2}Act_i^2 + \widehat{\beta_3}Cash_i + \widehat{\beta_4}PV_i + \widehat{\beta_5}Vol_i + \varepsilon_i$$

Using the number of transactions (Act_i) and its square (Act_i^2) without mean-centering for activity yields a high correlation between these two regressors (Table 1).

Table 1. VIF Statistics.

Variable	VIF Without Mean-Centering for Activity	VIF with Mean-Centering for Activity
Activity (Act)	10.73	2.06
Activity^2 (Act^2)	9.96	1.65
Average Cash Ratio	3.04	3.04
Portfolio Variability	2.71	2.71
Average Trade Size	2.11	2.11

In our final model, by expressing activity as deviations from its mean, the dependence between the linear and quadratic components is greatly reduced. The model retains the same explanatory power but becomes more reliable from an econometric point of view. Finally, using activity expressed as deviations from its mean allows a more reliable identification of the turning point. Conversely, it should be noted that the other explanatory variables do not exhibit problematic multicollinearity, as the Variance Inflation Factors (VIF) are moderate (between 2.11 and 3.04) and below the conventional benchmarks typically used. All regressions and statistical inference were conducted using Jamovi (Version 2.7.32). Summary statistics for all variables are reported in Table 2.

Table 2. Descriptive Statistics (Trader-Level Measures over the 4 h Simulation; N = 134).

Variable (with Mean-Centering for Activity)	Mean	Standard Deviation	Min	Median	Max
Performance (Return)	−0.1064%	0.2564%	−0.93%	−0.0717%	0.4834%
Activity	19.216 $(\overline{A})$	11.409	1	16.5	61
$Act_{c,i}$	0.000	11.409	−18.216	−2.716	41.784
$Act_{c,i}^2$	129.185	255.613	0.047	52.077	1745.86
Average Cash (euros)	59,870	21,470	20,006	59,480	99,990
Portfolio Variability	17,988.1	7527.33	0.000	18,679	38,271.7
Average Trade Size (€ per transaction)	10,876.1	5828.61	13.95	10,192.5	25,023.7

Variables: Performance (Return, %); Activity (total number of transactions); Average Cash (euros) is the average amount of cash held during the session; Portfolio Variability (SD of portfolio value, in euros, session); and Average Trade Size (euros/trade, session average). All measures are computed per trader over the full session. In the regression model, Average Cash Ratio is obtained by dividing Average Cash by the initial portfolio value of €100,000.

Descriptive statistics show high heterogeneity in trading behavior during the simulation. The total number of transactions shows considerable dispersion, suggesting styles ranging from very low participation to much more intensive activity. As expected, the activity variable expressed as deviations from its mean has a mean of zero, while $Act_{c,i}^2$ shows strong asymmetry, indicating the presence of a few participants who are particularly far from the activity mean. Performance is slightly negative on average, with significant variability. The average cash in the portfolio is high and varies greatly, confirming that some participants maintained high levels of cash while others were almost fully invested. The average trade size is also highly dispersed. Finally, the standard deviation of the portfolio value shows a large amplitude, but its interpretation remains difficult as it aggregates exposure, concentration and timing. Overall, these descriptive statistics corroborate the idea of a heterogeneous population, characterized by non-linear relationships between activity levels and performance, as well as by a variance in results that may be reinforced by the competitive nature of the simulation.

4.1. First Results

The correlation matrix highlights a negative relationship between performance and activity expressed as deviations from its mean, suggesting that around the average activity level, an increase in the number of transactions is associated with a decrease in average performance. By contrast, performance is not significantly correlated with the squared term. In other words, the convex effect could not be perceived by a direct comparison between these two variables. The correlations between performance and additional variables are weak, indicating that these variables play a controlling role rather than having a dominant effect on performance. Pearson correlations among the study variables are presented in Table 3.

Table 3. Pearson Correlation Matrix.

	Performance	$Act_{c,i}$	$Act^2_{c,i}$	**Average Cash Ratio**	**Portfolio Variability**	**Average Trade Size**
Performance	1.000	−0.49 ***	−0.102	−0.074	−0.048	−0.053
$Act_{c,i}$	−0.49 ***	1.000	0.613 ***	−0.079	0.15 *	−0.3 ***
$Act^2_{c,i}$	−0.102	0.613 ***	1.000	0.029	0.008	−0.167 *
Average Cash Ratio	−0.074	−0.079	0.029	1.000	−0.78 ***	−0.616 ***
Portfolio Variability	−0.048	0.15 *	0.008	−0.78 ***	1.000	0.534 ***
Average Trade Size	−0.053	−0.3 ***	−0.167 *	−0.616 ***	0.534 ***	1.000

* $p < 0.10$; *** $p < 0.01$.

$Act_{c,i}$, and $Act^2_{c,i}$ are naturally correlated, but this association is expected in a quadratic model and does not imply problematic collinearity. There is also a negative correlation between activity and average trade size, suggesting that the most active traders tend to break up their trades into smaller orders. Finally, the table reveals that average cash ratio is strongly and negatively correlated with portfolio variability and average trade size, while portfolio variability is positively correlated with average trade size. These patterns are consistent with an exposure risk-taking interpretation, contrasting a conservative profile (high cash holdings, lower portfolio variability and smaller trade sizes) with a more exposed profile. In summary, the variable linked to activity appears to be relatively distinct from the "risk" group, which supports the value of a model that separates the level of activity from the exposure. Results of the heteroscedasticity diagnostics are reported in Table 4.

Table 4. Heteroscedasticity Tests.

Test	**LM Statistic**	***p*-Value**	**F Statistic**	***p*-Value (F)**
Breusch–Pagan	11.277	0.0462	2.352	0.0443
White	37.814	0.00627	2.359	0.00281

Both tests indicate heteroscedasticity of the OLS model residuals. The Breusch–Pagan test is significant at the 5% level, suggesting that the variance of the errors depends on the explanatory variables (confirmed by White's test). Thus, homoscedasticity is unlikely to hold in our sample, which is consistent with a high degree of heterogeneity in trading behavior. Heteroscedasticity does not affect the consistency of the OLS coefficient estimates, but it can make classical standard errors unreliable, hence the interest in using robust standard deviations (HC3) and robust global tests for statistical inference. Moving from "classical" OLS to OLS with robust HC3 standard errors does not change the estimated coefficients. However, the standard deviations and therefore the t-statistics, p-values, confidence intervals and Fisher's F are recalculated taking heteroscedasticity into account. In practice, HC3 produces more conservative standard deviations, which may reduce the significance of some coefficients.

4.2. Results

The model explains a substantial share of the cross-sectional variation in performance ($R^2 = 0.493$; $R^2_{aj} = 0.473$) and is globally significant, including with the robust test ($F(5,128) = 16.72$, $p < 0.01$)). The coefficients on mean-deviation activity confirm a non-linear relationship between activity and performance: the first-degree term is negative and statistically significant, while the quadratic term is positive and statistically significant. This combination implies a convex curve: at low activity levels, increasing trading is associated with lower performance, while the marginal association becomes positive above a model-implied upper-tail level of activity. This pattern is compatible with heterogeneous trading profiles, but it does not identify the mechanism underlying high activity. A monotonic specification would only report the average (negative) association between activity and performance and would miss the turning point. The regression results are summarized in Table 5.

Table 5. Summary of Results.

Variable	Coeff. ($\widehat{\alpha}$,$\widehat{\beta}_i$)	SE (OLS)	t (OLS)	p (OLS)	SE (HC3)	t (HC3)	p (HC3)
Intercept	0.00507 ***	0.0014	3.576	0.0005	0.001811	2.8	0.006
$Act_{c,i}$	−0.000213 ***	0.00002	−10.47	6.53×10^{-19}	0.000024	−8.57	2.85×10^{-14}
$Act^2_{c,i}$	3.96×10^{-6} ***	8.102×10^{-7}	4.9	3×10^{-6}	9.7×10^{-7}	4.085	7.71×10^{-5}
Average Cash Ratio	−0.006313 ***	0.0013	−4.82	4×10^{-6}	0.001657	−3.81	2.15×10^{-4}
Portfolio Variability	-2.63×10^{-9}	3.53×10^{-8}	−0.075	0.941	4×10^{-8}	−0.065	0.948
Average Trade Size	-2.59×10^{-7} ***	4.02×10^{-8}	−6.45	2.1×10^{-9}	4.7×10^{-8}	−5.53	1.73×10^{-7}
Statistics							
N	134						
R^2	0.4929						
R^2_{adj}	0.4731						
Fisher (OLS), F(5, 128)	24.88 ***			1.885×10^{-17}			
Robust Fisher (Wald, HC3), F(5,128)	16.72 ***						1.092×10^{-12}

Stars indicate significance based on HC3 p-values (*** $p < 0.01$). SE (HC3) = robust standard errors of the HC3 type. Average Cash Ratio is measured as average cash holdings divided by the initial portfolio value of €100,000.

The control variables indicate that performance is also associated with exposure and trade implementation. Average cash holdings are negatively and significantly associated with performance. Given that the CAC 40 increased by approximately 0.30% during the session, this coefficient should be interpreted as an exposure-related result. Participants who held more cash were mechanically less exposed to the market movement. Therefore, the negative cash coefficient should be read as an association between underexposure and lower performance in a slightly rising market. The average trade size is also negative and statistically significant. This result indicates that participants who committed larger amounts per trade tended to achieve lower final performance, all else equal. However, average trade size does not directly identify whether participants held concentrated portfolios, traded repeatedly in the same security, or followed buy-and-hold rather than rebalancing strategies. In contrast, portfolio variability is not statistically associated with performance. Overall, the results support an association-based interpretation according to which a moderate increase in activity is accompanied, on average, by a deterioration in performance, while at higher levels of activity, higher trading intensity may be compatible with more active portfolio adjustment, although the mechanism cannot be directly identified with the available aggregate indicators in the context of the simulation. Moving from conventional OLS standard errors to HC3-robust standard errors does not change the coefficients, but it makes the inference statistically more conservative, while leaving the main conclusions unchanged (non-linearity of activity, negative effect of liquidity and average trade size, insignificance of portfolio variability).

The non-linearity between the level of activity and performance highlights the existence of a given level of activity at which the marginal effect of activity on performance equals zero before changing sign. To quantify this level and provide an economic interpretation of the estimated nonlinearity, we calculate the turning point of the relationship between activity and performance (Haans et al., 2016).

In the model where activity is expressed as deviations from its mean, the contribution of activity to performance is a function $f(Act_{c,i}) = \widehat{\beta_1} Act_{c,i} + \widehat{\beta_2} Act_{c,i}^2$. The turning point corresponds to the level of activity where the slope is zero, i.e., when

$$\frac{df}{dA_c} = \widehat{\beta_1} + 2\widehat{\beta_2} Act_{c,i}$$

We can deduce that

$$Act_c^* = -\frac{\widehat{\beta_1}}{2\widehat{\beta_2}}$$

Replacing with

$$\widehat{\beta_1} = -0.0002126$$

and

$$\widehat{\beta_2} = 0.000003960$$

we obtain

$$Act_c^* = -\frac{-0.0002126}{2 \times 0.000003960} = \frac{0.0002126}{0.00000792} = 26.84$$

We then express the turning point in terms of the number of transactions A by adding the mean:

$$A^* = \overline{A} + Act_c^* = 19.2164 + 26.84 = 46.06$$

In terms of interpretation, as $\widehat{\beta_2} > 0$, the parabola is convex: the point A^* therefore corresponds to a minimum. If $A < 46$ transactions, the slope is negative and an increase in activity is associated with a decline in performance, all other things being equal. Conversely, if $A > 46$ transactions, the slope becomes positive, and an increase in activity is associated with an increase in performance, ceteris paribus. In the estimated specification, the estimated relationship reaches its minimum at approximately 46 transactions. This value marks the point where the conditional marginal association changes sign in this sample. Because it lies in the upper tail of the activity distribution, its interpretation remains context-specific. The outcomes of the hypothesis tests are summarized in Table 6.

Table 6. Summary of the Working Hypothesis Test.

Hypothesis	Variable(s)	Expected Sign	Decision
H1: Convex relationship between activity and performance	$Act_{c,i}$ and $Act^2_{c,i}$	Negative ($Act_{c,i}$) and Positive ($Act^2_{c,i}$)	Validated
H2: Relationship between cash holdings and performance	Average Cash Ratio	Negative	Validated
H3: Relationship between average trade size and performance	Average Trade Size	Negative	Validated
H4: Non-directional effect	Portfolio Variability	No directional prediction	Not supported (no significant association)

4.3. Robustness and Sensitivity Analyses

The quadratic specification suggests a convex association between trading activity and performance. However, because the estimated turning point is in the upper tail of the activity distribution, additional sensitivity analyses are required (Appendix B). The baseline model implies a turning point of approximately 46.06 transactions, whereas the mean number of transactions is 19.22 and the maximum is 61. Only four participants are located above the estimated turning point. This indicates that the upward-sloping part of the fitted curve is identified from a small number of highly active participants. Consequently, the turning point should not be interpreted as a precise behavioral threshold, but as a model-implied value located in the upper tail of the observed activity distribution.

To assess the stability of the quadratic pattern, we conducted several robustness checks. First, leave-one-out estimations were performed by re-estimating the model after removing each participant one at a time. The signs of the linear and squared activity terms remained stable across these estimations: the linear activity coefficient remained negative, and the squared activity coefficient remained positive. The implied turning point varied between approximately 44.74 and 50.45 transactions. This suggests that the convex pattern is not entirely driven by a single observation.

Second, we estimated a robust regression using Huber weighting. This approach reduces the influence of observations with large residuals and provides a useful sensitivity check in a small and heterogeneous sample. The convex pattern was preserved, with an implied turning point of approximately 45.21 transactions. Third, we performed winsorized estimations. Under 1%/99% winsorization, the signs of the activity terms remained unchanged, and the turning point was approximately 45.98 transactions. Under stronger 5%/95% winsorization, the quadratic term became more fragile, and the implied turning point shifted to approximately 57.34 transactions. This result confirms that the upper-tail observations play an important role in identifying the upward-sloping part of the curve.

Finally, we estimated quantile regressions to examine whether the non-linear pattern is specific to the conditional mean. The median quantile regression preserved the convex structure, with a negative linear activity term, a positive squared activity term, and a turning point of approximately 46.14 transactions.

Overall, these sensitivity analyses support the existence of a convex activity–performance association in the data, but they also qualify its interpretation. The result is not driven by a single participant and remains visible across several alternative specifications. However, because only four participants are located above the estimated turning point, the positive marginal association beyond this level should be interpreted cautiously. It should be understood as evidence of conditional convexity in the upper tail of the sample, not as a general recommendation that higher trading activity improves performance. It is a model-implied level in a four-hour simulation with virtual capital, CAC 40 securities, ranking feedback, and a slightly rising market.

4.4. Top-Performer Comparisons

To further document the profile of the best-performing participants, we conducted additional comparisons between top performers and the rest of the sample; the results are reported in Table 7.

Table 7. Comparison between Top-Performing Participants and the Rest of the Sample.

Variable	Top 10% (n = 14)	Rest (n = 120)	p-Value	Top 20% (n = 27)	Rest (n = 107)	p-Value
Number of Transactions	12.0	20.1	0.0003	14.0	20.5	0.0040
Average Cash Ratio (%)	44.1%	61.7%	0.0003	47.5%	63.0%	0.0003
Portfolio Variability	22,905.0	17,414.4	0.0057	21,052.3	17,214.9	0.0340
Average Trade Size (euros per transaction)	13,844.7	10,529.8	0.0639	12,564.5	10,450.1	0.1496

Average Cash Ratio (%) is expressed as a percentage of the initial portfolio value. Average Trade Size is measured in euros per transaction.

Top performers are alternatively defined as participants in the top 10% or top 20% of final returns. Reported values are group means. p-values are based on mean-comparison tests between each top-performer group and the corresponding rest of the sample.

To better identify the profile of the best-performing participants, we performed additional comparisons using two definitions. Top performers were defined alternatively as the top 10% and the top 20% of final returns, and each group was compared with the rest of the sample. Across both definitions, top-performing participants executed fewer transactions on average, held lower average cash, and displayed higher portfolio variability than the rest of the sample. This pattern suggests that the strongest outcomes were associated with a combination of lower cash retention and greater portfolio exposure. It indicates that the upper part of the estimated non-linear relationship should not be interpreted as implying that the best-performing participants were simply the most active ones. The quadratic model should be interpreted as a conditional relationship: given average cash holdings, portfolio variability, and average trade size, the marginal association between activity and performance becomes positive only in the upper tail of the activity distribution. This does not imply that top performers traded more on average.

5. Discussion

Our results show that, in a short-term, competitive and incentive-based trading environment, activity does not have a monotonic effect on performance. These results are consistent with the works of De Bondt and Thaler (1985), Kaniel et al. (2008) and Gneezy and Potters (1997), which show that, depending on the informational and incentive context, the intensity of action and risk-taking can have different effects on performance. Our results suggest that activity may reflect heterogeneous behaviors (noise-driven trades, tactical rebalancing, and rank-improving strategies), suggesting that a monotonic relationship is unlikely. Our results show that the estimated relationship between activity and final performance is convex, with a negative first-degree term and a positive quadratic term, in line with the work of Coval et al. (2021) and Barber et al. (2009), as well as a turning point around 46 transactions. This configuration is consistent with an interpretation in which activity can be associated with different underlying patterns: at low to moderate levels, increased trading tends to reduce performance. Thus, at low or moderate levels of activity, the negative sign can be interpreted in the context of over-trading among individual investors. The increase in the volume of decisions may be consistent with overconfidence-related patterns, overestimation of the understanding of informational signals and the illusion of control (Langer, 1975; Odean, 1999; Barber & Odean, 2000). These biases are consistent with patterns where investors make too many decisions based on information signals that they are unable to process (Daniel et al., 1998). Activity may also be associated with non-informational motivations (sensation seeking, excessive optimism), which underscores that trading volume is not necessarily associated with value creation (Statman et al., 2006; Grinblatt & Keloharju, 2009). In our context, the time constraint (four hours) and the ranking objective may be associated with greater pressure to act and with higher trading frequency that appears more behaviorally driven than optimization-based (Payne et al., 1988). However, once activity exceeds a given level, it may be compatible with more structured adjustment, although this mechanism is not directly identified by the available indicators. It should be noted that our results are based on a slightly bullish market environment during the simulation, which may be associated with better outcomes for highly exposed portfolios and for participants who adjusted their positions quickly. In such an environment, part of the increase in activity may be due to trend following and alignment with positive market dynamics (De Long et al., 1990). The presence of a turning point suggests that high activity is not exclusively indicative of inefficient overtrading (Hendershott et al., 2011). This interpretation is consistent with findings from experimental securities markets, where performance is often tied to information processing and adaptive behavior rather than to average exposure alone (Plott & Sunder, 1982). In practice, the convexity can be interpreted as statistical evidence of profile heterogeneity: some participants overtrade under bias and competitive pressure, while another subset displays a pattern in which high activity is conditionally associated with better performance. The robustness analyses also refine the interpretation of the quadratic relationship. Although the convex pattern is preserved across several sensitivity checks, the upward-sloping part of the relationship is based on a small number of highly active participants. The turning point should not be interpreted as a general behavioral level or as evidence that the best-performing participants traded the most. It indicates that, conditional on the controls included in the model, the marginal association between activity and performance becomes positive in the upper tail of the activity distribution. This finding is compatible with heterogeneous trading patterns. However, it does not identify the psychological or strategic mechanisms behind these patterns.

This interpretation should be distinguished from studies that directly measure investor perceptions. For example, Hoffmann et al. (2015) link investor perceptions to actual trading and risk-taking behavior by combining perception measures with brokerage records. Our design does not include comparable perception measures. Our results should be interpreted as associations between trading indicators and performance.

The top-performer comparisons further qualify the interpretation of the quadratic model. Participants in the top 10% and top 20% of final performance executed fewer transactions on average than the rest of the sample, while holding less cash. Thus, the best-performing participants were not simply the most active ones. The quadratic model should be read as a conditional result: given cash holdings, portfolio variability, and average trade size, the marginal association between activity and performance becomes positive in the

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upper tail. This conditional convexity does not imply that high activity characterizes the best-performing group.

One specific feature of the experiment is relevant for interpreting these results. Participants faced no personal financial loss, which may be associated with a greater willingness to pursue riskier strategies. This situation corresponds to contexts where the absence of 'real' losses or the perception of 'unrealized gains' may be associated with increased risk-taking, in line with the mechanisms described by prospect theory when evaluation is based on perceived gains and losses rather than on final performance (Kahneman & Tversky, 1979; Thaler & Johnson, 1990). In other words, some of the additional trading may reflect context-specific incentives inherent to the simulation environment rather than stable investment preferences. The psychological propensity to "take a chance" is high when the cost of being wrong is low. At the same time, the tournament-style incentive scheme and continuous ranking feedback may have contributed to the context in which trading heterogeneity emerged. However, because all participants faced the same incentive and feedback structure, these features cannot be interpreted as separately identified causal mechanisms. They should be understood as elements of the experimental institution. This interpretation is consistent with the experimental asset-market literature, which shows feedback structures are part of the market environment in which decisions are made (Füllbrunn et al., 2014). Thus, the results should not be interpreted as estimates of a tournament effect (Lazear & Rosen, 1981; Brown et al., 1996; Basak & Makarov, 2014; Busse, 2001). Part of the trading behavior may reflect responses to competitive pressure and relative-performance incentives rather than behavior that would arise in a standard setting. At the same time, relative-performance logics such as benchmarking, ranking, and performance-based rewards are also present in some trading and portfolio-management environments. However, because all participants were exposed to the same incentive scheme, our design does not identify a distinct tournament effect.

An additional explanation for this convexity may lie in feedback dynamics during the session. Learning and timing are central when interpreting the relationship between trading experience and performance (Nicolosi et al., 2009). Early gains may be associated with stronger commitment and confidence, and with higher subsequent activity among some participants, while initial losses may discourage some participants or trigger recovery attempts when improving rank appears unlikely. This dynamic is consistent with the possibility of heterogeneous behavioral responses within the sample: some participants may become less engaged after early negative results, whereas others may intensify their involvement after initial success. Reinforcement dynamics may plausibly operate in this type of competitive setting, where interim gains or losses could influence subsequent trading intensity. However, testing such a mechanism would require sequential participant-level observations and a dynamic specification (Seru et al., 2010). Since our study relies on session-level aggregated variables, these effects cannot be identified in the current empirical framework. This interpretation, which is also consistent with learning and performance-attribution mechanisms (Weiner, 1985), should be understood as a plausible explanation instead of being tested in our study.

Regarding control variables, average cash ratio is negatively associated with performance. This result should be interpreted considering the market context. Since the CAC 40 increased by approximately 0.30% during the session, participants who held more cash were mechanically less exposed to market movement. The negative coefficient should be interpreted as an underexposure effect in a rising market, rather than as evidence of a poor behavioral style. In a different market environment, the same cash-holding behavior could have different performance implications.

Average trade size is also negatively and statistically associated with performance. This finding suggests that the implementation of trades matters in addition to trading frequency and exposure. Participants who committed larger amounts per transaction tended to perform less well, conditional on the other variables. However, average trade size remains a coarse indicator. It may be compatible with more concentrated execution or less gradual adjustment, but it does not directly measure portfolio concentration, turnover, holding-period strategies, or repeated trading in the same security. For this reason, the coefficient should not be interpreted as direct evidence of poor diversification or overconfidence. The findings have implications for the design of trading simulations and investor-education environments. Since participants operated with visible rankings, feedback, and virtual capital, the results suggest that how information and performance signals are presented may shape novice trading patterns. This point is consistent with Mugerman et al. (2022), who show that the emphasis placed on risk can affect retail investor attention and financial decisions. In educational trading simulations, rankings and feedback should be designed carefully, so that they encourage learning and risk awareness rather than stimulating excessive activity or performance chasing.

In contrast, portfolio variability is not statistically significant. Given the short duration of the session and the nature of this proxy, this variability measure does not show a significant association with performance. In addition, this indicator may combine several dimensions, including exposure, concentration, and unstable portfolio adjustments, which can attenuate its relationship with performance. Its non-significance suggests that this proxy does not deliver a statistical signal in our specific design.

Econometric diagnostics reinforce the robustness of the inference. The Breusch–Pagan and White tests reject homoscedasticity, which is consistent with high individual heterogeneity and justifies the use of robust standard deviations, in particular HC3 in small to moderate samples (Breusch & Pagan, 1979; White, 1980; MacKinnon & White, 1985; Long & Ervin, 2000). Furthermore, expressing activity as deviations from its mean improves the stability of the estimates by reducing collinearity between the first-degree term and its square, thereby yielding a turning point that is more economically interpretable.

6. Conclusions

This article examines a behavioral finance question in the context of an incentivized trading experiment: is trading activity linked to performance, and is this relationship non-linear once exposure is considered? The evidence indicates that trading activity is associated with performance in a non-linear way. The quadratic specification highlights a convex dynamic and a model-implied upper-tail turning point corresponding to approximately 46 transactions. This turning point is context-specific and should not be read as a general trading rule for novice investors. This relationship indicates that trading frequency is not associated with homogeneous behavior. Depending on the level of activity, it may reflect different trading patterns rather than a single behavioral process.

The experimental design helps contextualize this interpretation. The four-hour duration creates a high-frequency decision-making environment: participants must arbitrate quickly, with limited time for analysis and intense exposure to information and intraday fluctuations. Under these conditions, the literature shows that individuals rely more on heuristics, with context-sensitive judgements, which can affect the quality of decisions (Tversky & Kahneman, 1974). Secondly, a virtual capital of 100,000 euros alters participants' decision context: the absence of real financial losses may be associated with less disciplined or more aggressive trading patterns, as the "pain" of losses is less present than for a personal financial investment. This difference between simulated and real-financial decision environments is consistent with the idea that emotions and affective evaluation can influence trading behavior (Loewenstein et al., 2001). Finally, the incentive structure creates a competitive context that may be associated with behavioral differences: when the reward depends on ranking, optimization becomes relative and may be associated with more aggressive strategies, regardless of the expected gain. This type of environment accentuates social comparisons and the focus on relative performance, which is likely to alter the dynamics of decision-making (Barberis & Thaler, 2003). However, because the tournament incentives and continuous feedback are identical for all participants, our data do not identify a distinct "tournament effect." Tournament-based interpretations are presented as contextual framing, and the contribution of the incentive scheme cannot be separately identified from other features of the setting.

In this context, the convex relationship can be understood as evidence consistent with heterogeneous trading patterns: an initial intensification that may reflect decision-making influenced by heuristics and, beyond a certain level, more structured activity is associated with a more favorable performance pattern in our setting. The fact that performance is also linked to the percentage of cash and the average size of transactions highlights that the explanation is not solely related to the frequency of movements. It also involves choices of exposure and implementation of decisions. Methodologically, the approach selected (activity expressed as deviations from its mean, non-linear specification) provides an economically interpretable reading of a phenomenon that is often discussed in qualitative terms ("too much trading can be harmful"). Overall, the study shows that short-horizon stock-market simulations generate large heterogeneity in trading behavior. These findings should be interpreted within a specific setting characterized by novice participants, short decision horizons, and relative-performance incentives. Although this setting is bounded, it reflects a competitive logic that is also present in some segments of portfolio management, where relative-performance incentives and tournament behavior have been documented (Brown et al., 1996; Li et al., 2022).

7. Limitations

This study has several limitations that should be considered when interpreting the results and determining their scope. First, external validity is constrained by the composition of the sample. The participants were 134 second-year undergraduate students in Management Sciences from a single university, which implies limited demographic diversity and a relatively homogeneous level of financial training. Even if this choice is consistent with our objective of studying short-horizon behavior among novice participants, it does not support behavioral generalization to professional investors. The findings are relevant to novice participants at the first stage of participation in stock-market environments, when trading discipline, market familiarity, and behavioral adjustment are still developing. It should also be noted that we did not include sociodemographic variables or personality traits. This omission reflects a deliberate choice as our aim was to focus on trading styles rather than on individual characteristics. Secondly, the period is very short, so the performance measured reflects intraday dynamics rather than longer-term investment skills. The interpretation of the cash coefficient is also conditional on the market trend during the session. Because the CAC 40 increased slightly over the four-hour window, holding cash mechanically reduced exposure to the positive benchmark movement. The result should therefore not be generalized to flat or declining market conditions. Thirdly, the use of virtual money means that there are no real monetary losses, which may reduce discipline and encourage more extreme behavior (higher trading intensity and more concentrated positions) than in a context where the capital is private. Accordingly, the results should be interpreted as trading patterns in an incentive-driven simulation rather than as a direct representation of investment choices under actual financial exposure. Fourthly, the academic incentive system and ranking logic are part of the experimental environment. Since all participants were exposed to the same incentive and feedback structure, the study cannot isolate the causal effect of tournament incentives or continuous rankings. These features should be interpreted as contextual conditions rather than as separately identified mechanisms. Fifthly, measuring portfolio variability through portfolio standard deviation aggregates several dimensions and does not distinguish between market risk and portfolio-specific risk. A related limitation concerns average transaction size. This variable does not measure portfolio concentration, the number of distinct securities held, turnover, average holding period, or the share of repeated trades in the same security. Consequently, the negative coefficient on average transaction size should not be interpreted as evidence of poor diversification or overconfidence. Sixthly, the empirical model focuses on the reduced-form association between trading indicators and performance. Because the simulation is dynamic and the empirical model relies on session-level aggregate variables, the direction of the relationship cannot be established. Activity may be associated with performance because trading decisions affect returns, because interim gains or losses affect subsequent trading or because both are driven by unobserved participant characteristics. The estimates should be interpreted as reduced-form associations rather than causal effects. Seventhly, a limitation concerns the non-sequential treatment of performance: we observe performance at the end of the simulation, without modeling intra-session developments, and many behavioral mechanisms can emerge over the course of the session. For example, poor performance may induce reactive trading, and losses can result in trading adjustments, so the direction of causality cannot be established with our data. Because we do not model within-session dynamics, the OLS estimates should be interpreted as reduced-form associations rather than causal effects. Finally, the empirical model does not measure cognitive biases. The study does not include post-simulation questionnaires, psychometric measures, or direct indicators of overconfidence, illusion of control, attention, risk tolerance, beliefs, expectations, or learning. Such measures would be necessary to test the behavioral mechanisms underlying the trading patterns. Consequently, the estimated relationships should be interpreted as associations between trading indicators and performance.

8. Avenues for Further Research

Several extensions could build on our results and better clarify the underlying mechanisms. Firstly, a sequential analysis of performance (using the value of the portfolio at regular intervals) would make it possible to examine the underlying processes: periods of value creation versus destruction, phases of recovery after losses, reactions to market moves. From this perspective, it would be useful to distinguish between different types of trajectories (gradual progression, high volatility, last-minute strategies). Secondly, trading styles could be broken into more detailed components (stock selection, timing, portfolio rotation, concentration) by adding indicators of turnover, number of stocks held, concentration index, average holding period and the share of repeated trades in the same security, to identify whether the activity "pays off" through better selection, better timing or simply risk-taking. Thirdly, the econometric approach could incorporate interaction effects (e.g., activity and liquidity) and more developed non-linear forms to test whether the positive effect above the turning point only appears under some exposure configurations.

Fourthly, heteroscedasticity suggests a high degree of heterogeneity in trading styles. Segmentation approaches would make it possible to verify whether the U-shaped relationship is driven by the upper part of the distribution (best portfolios), by extreme behaviors, or whether it is stable across the entire sample.

Fifth, to link trading patterns to behavioral finance mechanisms, the integration of psychometric measures, or even personality traits, would make it possible to test

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whether the most active low-performance profiles are those with the highest scores for overconfidence, and whether "efficient" activity above the given level corresponds more to disciplined profiles.

Sixth, a further extension would be to exploit the experimental design by varying the incentives: comparing a fixed bonus with a tournament-type incentive, introducing a reward based on risk-adjusted return, or adding higher transaction costs to assess how these parameters alter the relationship between activity and performance and the turning point.

Finally, assessing the external validity of the findings could involve replication across different populations and contexts (other securities universes, contrasting volatility conditions) to determine whether the convexity and turning point observed constitute a stable regularity or a characteristic specific to the simulation context. These extensions would provide a more detailed understanding of the elements (incentives, biases, execution and temporal dynamics) that structure performance in simulated trading.

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Appendix A. Participant Instructions and Platform Description (ABC Bourse Simulation)

The instructions below were provided to participants prior to the start of the simulation and were also summarized orally by the instructors.

(1) Overview and objective

Participants took part in a four-hour trading simulation using the ABC Bourse platform. Each participant managed an individual virtual portfolio and could place trades at their discretion throughout the session. The objective was to maximize portfolio value over the session horizon under the incentive scheme described in the main text.

(2) Trading Environment

- Individual trading: Participants did not trade directly with each other. Orders were placed individually and executed through the platform at the prevailing market price.
- Real-time market prices and information: The platform provided real-time market prices and real-time market information during the session, enabling participants to monitor quotations and portfolio evolution continuously.
- Investable assets: Participants could trade equities of firms included in the CAC 40 index (French large-cap constituents).
- Short selling was not allowed: Participants could only take long positions (buy then sell).

- Initial capital: Each participant started with a virtual capital of €100,000.
- Trading horizon: The simulation lasted four hours, during which participants could place as many trades as they wished, subject to the platform's rules and constraints.

(3) Trading actions and execution

Participants could:

1. Buy eligible CAC 40 equities using available cash;
2. Sell holdings previously purchased;
3. Hold cash and maintain positions without trading;
4. All transactions were recorded by the platform and contributed to the final portfolio value at the end of the session.

(4) Portfolio monitoring and feedback

Participants could track their portfolio value and composition throughout the session. Consistent with the competitive setting described in the manuscript, rankings and performance feedback were available during the session as implemented by the platform and the simulation protocol.

(5) Rules and constraints

- No short-selling.
- No trading of assets outside the CAC 40 investable list.
- Trades executed at real-time prices with real-time information access.
- Individual decision-making: each participant controlled only their own portfolio.

(6) Data recorded

The platform recorded transaction histories and portfolio states used to compute trader-level indicators (number of transactions, average transaction size, average cash holdings, portfolio value and its variability).

Appendix B. Robustness and Sensitivity Checks

This appendix reports additional robustness and sensitivity checks for the quadratic activity–performance specification. The purpose of these checks is to assess whether the estimated convex relationship is driven by influential observations, extreme values, or the use of a conditional-mean model.

Table A1. Robustness and sensitivity checks.

Robustness Check	Purpose	Main Result	Interpretation
Baseline HC3 model	Main heteroscedasticity-robust specification	Turning point = 46.06 transactions	Baseline convex association
Number above turning point	Distributional check	4 participants above threshold	Upward branch located in upper tail
Leave-one-out estimation	Tests dependence on single observations	Signs remain stable; turning point = 44.74–50.45	Not driven by one participant
Huber robust regression	Reduces influence of large residuals	Convexity preserved; turning point = 45.21	Robust to residual outliers
Winsorization 1%/99%	Mild extreme-value correction	Convexity preserved; turning point = 45.98	Robust to mild winsorization

Table A1. *Cont.*

Robustness Check	Purpose	Main Result	Interpretation
Winsorization 5%/95%	Stronger sensitivity check	Quadratic term weaker; turning point = 57.34	Upper tail matters for identification
Median quantile regression	Tests median rather than mean relation	Convexity preserved; turning point = 46.14	Pattern not limited to conditional mean

These checks show that the signs of the linear and quadratic activity terms are generally stable. However, the stronger winsorization result indicates that the quadratic pattern depends partly on the upper tail of the activity distribution. This is consistent with the fact that only four participants are located above the estimated turning point. For this reason, this article interprets the turning point cautiously as a model-implied upper-tail value rather than as a precise behavioral threshold.

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