Designing Trading Simulations for Learning: Ranking Feedback, Tournament Incentives, and Behavioral Responses

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Abstract

Trading simulations are widely used in finance education, but their pedagogical effects depend on instructional design. Competitive rules and performance feedback may shape trading behavior. This study examines a classroom intraday trading simulation involving CAC40 stocks in which students operated under a continuously updated ranking and a Top 3 reward scheme, creating a rank-order tournament with pedagogical issues. Using data from 133 students, we analyze performance heterogeneity through a distribution-sensitive methodology that combines quartile and extreme-group profiling with quantile regressions.

The results show that excessive trading activity is associated with lower-ranking outcomes, while sustaining top-ranking performance strongly depends on maintaining sufficient market exposure. These findings indicate that different segments of the ranking distribution are shaped by different behavioral mechanisms, which mean-based analyses may fail to capture. We also incorporate OCEAN personality traits to support a profiling perspective. Personality traits help identify localized behavioral differences across distribution segments even if they did not represent a uniform predictor of performance.

For financial educators, continuously visible rankings and tournament-style rewards should be treated as instructional design choices, not purely evaluative tools. They can increase engagement and may also intensify over-activation and suboptimal decisions unless paired with structured debriefing and behavioral supports.

Keywords: trading simulation, financial education, tournament incentives, ranking feedback, overtrading, behavioral finance, quantile regression, OCEAN personality traits

JEL: A22; G11; G41; C21

1. Introduction

Trading simulations make financial concepts (market exposure, portfolio risk, order execution, and performance measurement) operational through repeated decision-making. Simulations are useful for revealing how novices cope with time pressure, and gains and losses, and how they translate "what they know" into "what they do." For finance instructors, this pedagogical value creates a design challenge as much as an opportunity: the same features that make simulations engaging may also induce behaviors that can distort both learning processes and performance. The teaching-and-learning literature has emphasized that the value of simulations depends on design rules, incentives, feedback, and evaluation structures, because they shape the behaviors through which learners engage (Kolb, 1984; Garris et al., 2002; Fink, 2013).

Our study addresses the behavioral patterns induced when a trading simulation combines continuously visible rankings with a top-3 reward rule, and what does this imply for simulation design and formative feedback? By focusing on how incentives and feedback architecture shape trading behaviors, this paper has implications for finance learning environments and to the conditions under which simulations support behavioral discipline.

A central behavioral-finance framework for interpreting trading simulation is overtrading. Higher trading frequency tends to be associated with inferior performance, especially among individual investors (Odean, 1999; Barber & Odean, 2000). Overtrading has been linked to cognitive and motivational mechanisms, including overconfidence and the tendency to overweight some signals (Daniel et al., 1998), as well as an action bias, a preference for doing something rather than waiting (Patt & Zeckhauser, 2000).

In our setting, students participate in a four-hour intraday simulation on CAC40 constituents with a rule that is announced ex ante: academic bonus points are awarded to the top three portfolios. This structure corresponds to a rank-order tournament, in which payoffs depend on relative rather than absolute performance (Lazear & Rosen, 1981). Agents rationally become sensitive to rank positions and may adopt “catch-up” strategies that increase the probability of extreme outcomes (Brown et al., 1996; Chevalier & Ellison, 1997; Basak et al., 2007). In our setting, rankings are displayed and updated continuously throughout the session. Continuous rank feedback turns social comparison into a reference point and transforms each rank movement into a signal that can result in reactive behavior.

On the one hand, our design can induce predictable biases as students respond to rank feedback and competitive pressure (Odean, 1999; Barber & Odean, 2000; Lazear & Rosen, 1981). On the other hand, the design provides a basis for formative assessment: instructors can structure post-simulation reflection around interpretable profiles, connect these profiles to behaviors, and implement framing and support mechanisms. It aligns with principles of experiential learning (Kolb, 1984) and with evidence that simulations generate learning gains when followed by guided debriefing (Fanning & Gaba, 2007; Deterding et al., 2011; Hamari et al., 2014).

The tournament logic has consequences for research design and statistical strategy. Focusing on mean relationships can be misleading because the question is distributional: what differentiates students who fall into the bottom of the ranking from those who reach (and hold) the top? Put differently, the drivers of “not getting stuck at the bottom” may differ from the drivers of “reaching the top.” We adopt a profiling approach analyzing rank-relevant contrasts and heterogeneity across the performance distribution. We combine comparisons (Top10% vs Bottom10%) and quartile partitions with quantile regressions at q = 0.10/0.90 and q = 0.25/0.50/0.75 (Koenker & Bassett, 1978).

Our research question is as follows: in an intraday trading simulation with continuously visible rankings and tournament-style rewards, which behavioral and individual factors are associated with performance across the ranking distribution, and what do these patterns imply for the design of future trading simulations?

This paper makes two main contributions. First, it provides evidence that visible rankings and reward schemes shape students’ trading behavior, yielding guidance for instructors on how tournament-style course designs can amplify suboptimal choices. Second, it offers an interpretation of performance by combining quartile and decile profiling with quantile regressions, showing that determinants vary across the distribution.

2. Hypothesis

In a setting with a rank-order tournament, the behaviorally relevant objective is to reach upper ranks where rewards are concentrated (Lazear & Rosen, 1981). Tournament incentives can increase the attractiveness of strategies that raise the probability of extreme outcomes (Brown et al., 1996; Chevalier & Ellison, 1997; Basak et al., 2007). In addition, social comparison may amplify short-horizon reactivity. Accordingly, our hypotheses are formulated around three ideas: rank-relevant behavioral mechanisms, distributional heterogeneity and profiling expectations.

H1. Over-Activation and Lower Rank Performance

Higher trading intensity is expected to be associated with lower relative performance and a lower probability of belonging to the top of the ranking. This expectation follows overtrading literature, which shows that frequent trading is associated with lower performance (Odean, 1999; Barber & Odean, 2000) and is consistent with mechanisms such as overconfidence and action bias (Daniel et al., 1998; Patt & Zeckhauser, 2000). In a tournament with continuously visible rankings, students responding to rank declines may engage in reactive “catch-up” trading, even when such behavior is counterproductive. It implies higher activity in lower-ranking groups and a negative association between activity and performance.

H2. Under-Exposure and Reduced Access to Top Ranks

Higher average cash holdings are expected to be associated with lower relative performance, with relevance for access to upper-tail ranking outcomes. In tournament settings, rewards are concentrated at the top, making overly defensive positioning costly when moving up the ranking requires generating a performance differential (Lazear & Rosen, 1981; Brown et al., 1996; Chevalier & Ellison, 1997). In an intraday simulation, cash directly limits participation in market movements. Remaining too liquid may reduce discomfort but reduce the probability of outperforming peers. We expect a negative association between cash holdings and performance.

H3. Portfolio Risk as a Marker of Tail Outcomes

Portfolio risk is expected to function primarily as a marker of extreme outcomes, rather than as a stable monotonic determinant of ranking position. Tournament incentives may encourage risk shifting that increase dispersion and tail probability without improving expected performance (Brown et al., 1996; Chevalier & Ellison, 1997; Basak et al., 2007). As a result, higher risk may appear in both very strong and very weak outcomes, rather than showing a linear relationship with ranking position once activity and exposure are accounted for. This implies possible non-monotonic patterns across quartiles and unstable quantile-regression effects.

H4. Tail Heterogeneity in Performance Mechanisms

The determinants of performance are expected to differ across the distribution: trading activity should be more informative in the lower tail, whereas exposure should become informative in the upper tail. Students near the bottom may become increasingly reactive to rank declines, amplifying action bias and unproductive trading (Patt & Zeckhauser, 2000; Odean, 1999). By contrast, students competing for top ranks need sufficient market participation to generate outperformance, making under-exposure particularly costly near the upper tail (Lazear & Rosen, 1981; Brown et al., 1996).

H5. Profiles Individual Characteristics (Demographics and Personality Traits) as Localized Moderators of Rank-Relevant Profiles

We expect demographic variables (age, gender) and OCEAN traits to act as localized moderators of rank-relevant behavioral profiles, with effects more likely to appear in top-versus-bottom comparisons or specific quantiles than as stable linear effects across the full performance distribution. This expectation is consistent with differential psychology, which conceptualizes traits as dispositions that influence the likelihood of certain responses under specific contexts rather than as deterministic causes of outcomes (John & Srivastava, 1999; McCrae & Costa, 2008). In our setting, tournament feedback may interact with individual differences in self-regulation, competitive responsiveness, and prior maturity or experience proxies (e.g., age), shaping the probability of adopting profiles such as over-activation or reactive chasing. Because prior evidence on short-horizon trading performance is mixed and context-sensitive, we do not impose directional predictions for age or gender (Cheng et al., 2013). We examine these variables within a profiling framework, emphasizing group differentiation and quantile heterogeneity, with cautious interpretation.

3. Methodology

3.1 Experimental Design and Instructional Setting

The study is based on a four-hour intraday trading simulation implemented through a stock-market game created on ABC Bourse. The simulation was conducted on December 11, 2025, from 1:30 p.m. to 5:30 p.m. Participants were given an identical virtual portfolio of €100,000 and made buy and sell decisions in an environment where portfolio value was observable throughout the session. To preserve market realism, each order carried a 0.2% transaction cost. This parameter makes trading frequency directly costly and strengthens the behavioral relevance of an overtrading interpretation when activity becomes excessive.

There was no explicit limit on the number of orders and no explicit cap on aggregate transaction volume during the session. This absence of constraints allows spontaneous trading styles to emerge in response to the incentive and feedback structure, rather than being compressed by operating rules. At the same time, because the participants were novice learners, the instructional environment had to remain sufficiently structured and cognitively manageable which is consistent with established work on novice learning and task design (Sweller, 1988; Mayer, 2004; Kirschner et al., 2006).

Transactions were restricted to equities of firms included in the CAC40 French Index. CAC40 constituents represent a familiar set of large firms, which lowers entry barriers for novices. Methodologically, restricting the universe to CAC40 equities also helped reduce inequity in prior experience: allowing more complex instruments would likely have given an advantage to students with prior experience. The tradable universe was calibrated to support comparability across participants while preserving an authentic decision context (Ambrose et al., 2010).

Participants were second-year undergraduate students in Management Sciences at a Belgian university. The simulation was integrated into the course Introduction to Financial Reality, which is the first finance course in their curriculum. Participants should be considered as novices because they had only limited prior exposure to financial concepts, instruments, and decision-making routines, and little (if any) direct trading experience.

The core design feature is the joint structure of incentives and feedback. First, a participation-based academic bonus was awarded for taking part (0.5 point on the exam), ensuring a common incentive for engagement. Second, an additional performance-based bonus was awarded to the three highest-ranked portfolios, under a rule announced in advance: 2.0 points for the first place, 1.5 points for the second place, and 1.0 point for third one. Despite these incentives, participation remained partial: only 133 of the 218 students enrolled in the course took part (61.0%). Finally, rankings were displayed and updated continuously. From an instructional-design perspective, continuously visible ranking functions as a high-frequency feedback channel, which affects learner regulation and strategy adaptation (Shute, 2008; Nicol & Macfarlane-Dick, 2006).

3.2 Data, Variables, and Data Preparation

The sample consists of 133 participants. Performance is defined as the portfolio's final return over the simulation session (i.e., final performance relative to the initial capital). The explanatory variables are organized into three groups: trading behavior and market exposure, portfolio risk, and individual characteristics.

Trading behavior and exposure are captured through the total number of transactions, average cash holdings during the session (used as a proxy for market exposure, with lower cash holdings indicating higher exposure), and average transaction size (used as an indicator of position intensity per order). Portfolio risk is measured by the standard deviation of portfolio value. Individual characteristics include age, gender (coded as a binary indicator: Male = 1), and the five OCEAN personality traits (see Appendix).

To improve comparability across predictors measured in different units (proportions, monetary values, and psychometric scores), continuous variables used in the quantile regression models are standardized as z-scores. This transformation facilitates interpretation of coefficient magnitudes across predictors without altering the sign or statistical significance of the estimated associations. The gender variable is kept as an unstandardized binary indicator (Male = 1, Female = 0). Descriptive statistics and group comparisons are reported in original units for substantive clarity.

Table 1. Descriptive Statistics of Study Variables

Variable	**Mean**	**SD**	**Min**	**Median**	**Max**
Outcome Variable					
Return	-0.0011	0.0026	-0.0093	-0.0007	0.0048
Trading Behavior and Market Exposure					
Activity (Number of Transactions)	18.98	11.11	1.00	16.00	61.00
Average Cash Holdings (Proportion of Cash in the Capital)	0.6	0.215	0.2006	0.5972	0.9999
Average Transaction Size	10,936.32	5,808.66	13.95	10,229.76	25,023.65
Risk (Standard Deviation of Portfolio Value)	17,983.42	7,555.59	0.00	18,729.8	38,271.7
Individual Characteristics					
Age (Years)	20.90	3.48	18.00	20.00	42.00
Gender (Male = 1)	0.579	0.496	0.000	1.000	1.000
Openness	32.35	5.59	18.00	32.00	45.00
Conscientiousness	30.71	5.90	12.00	30.00	45.00
Extraversion	24.64	5.90	9.00	24.00	40.00
Agreeableness	38.31	5.39	24.00	39.00	48.00
Neuroticism	21.74	6.56	8.00	22.00	35.00

Table 1 shows substantial heterogeneity in behavior during the simulation. The wide dispersion in transaction numbers and average cash holdings indicates that students responded very differently to the same environment, which is pedagogically important in a novice cohort. These descriptive patterns also support the study's focus on activity and market exposure as central behavioral dimensions. More generally, the variability across behavioral and individual characteristics justifies the use of a distribution-sensitive strategy rather than relying on average effects.

3.3 Analytical Strategy: A Ranking-Profiling Approach

We characterize the behavioral profiles associated with ranking positions by combining three levels of analysis: extreme-group contrasts, quartile-based profiling and distribution-wide heterogeneity using quantile regressions.

3.3.1 Top–Bottom Comparison

We first define two extreme groups: the Top10% (the 13 highest returns) and the Bottom10% (the 13 lowest returns). This comparison is designed to identify the mechanisms that distinguish top-ranking outcomes from low-ranking outcomes, which is relevant in a tournament environment where rewards are concentrated at the upper of the ranking.

For each variable (activity, cash holdings, risk, average transaction size, age, gender, and OCEAN traits), we report group means (and standard deviations) and perform two complementary tests: a Welch test (difference in means under unequal variances) and a Mann–Whitney test (nonparametric tool for skewed distributions and small samples). Using both parametric and nonparametric tests reduces reliance on strong distributional assumptions and provides a more robust reading of top-versus-bottom contrasts. Given the limited size of the extreme groups (n = 13), these results are interpreted as profiling evidence rather than as causal evidence.

3.3.2 Quartile-Based Profiling

We extend the analysis to a three-group partition based on return quartiles: Top25% (n=33), Middle50% (=67), and Bottom25% (n=33). The purpose is to assess whether the variables that separate the extremes also help structure ranking positions across the broader sample. We report descriptive statistics for each group and conduct a Welch ANOVA (to test mean differences across three groups under potentially unequal variances) together with a Kruskal–Wallis test (nonparametric test of group distribution differences). To preserve a direct reading consistent with tournament logic, we also report a Top25% vs. Bottom25% contrast using Welch and Mann–Whitney tests. This quartile-based analysis helps connect extreme cases to the broader range of behavior.

3.3.3 Distribution Analysis: Quantile Regressions

Finally, to analyze performance across the distribution, we estimate quantile regressions (Koenker & Bassett, 1978). Two sets of quantiles are examined: extreme quantiles (q = 0.10 and q = 0.90), which capture mechanisms associated with underperformance and high performance and central quantiles (q = 0.25, q = 0.50, q = 0.75).

In all models, the dependent variable is the return, and predictors include behavioral and portfolio variables, individual characteristics and OCEAN traits.

4. Results

4.1 Top–Bottom Comparison

Consistent with the tournament logic of the simulation, we begin with a comparison between the 13 best and the 13 worst returns. This first step is designed to identify the mechanisms associated with the contrast between top-performing and bottom-performing outcomes.

Table 2. Top10% (n=13) vs. Bottom10% (n=13)

Variable	**Top10% (Mean, SD)**	**Bottom10% (Mean, SD)**	**p (Welch)**	**p (Mann–Whitney)**
Number of Transactions	12.31 (6.17)	31.23 (7.68)	4.73e-07***	4.482e-05***
Average Cash Holdings	0.426 (0.125)	0.567 (0.169)	0.02402**	0.01198**
Risk	22,971.69 (6,275.92)	21,874.48 (3,922.91)	0.5988	0.8777
Average Transaction Size	14,209.02 (5,990.32)	12,895.91 (4,058.62)	0.5200	0.6444
Age	23.38 (6.27)	20.15 (2.70)	0.1068	0.006898***
Gender (Male=1)	0.846 (0.376)	0.846 (0.376)	1.0000	1.0000
Openness	32.31 (5.19)	34.77 (5.37)	0.2462	0.2070
Conscientiousness	32.31 (7.00)	26.92 (5.63)	0.04148**	0.0764*
Extraversion	24.92 (5.66)	26.23 (4.95)	0.5369	0.5373
Agreeableness	38.85 (4.02)	37.46 (5.52)	0.4722	0.5199
Neuroticism	18.00 (5.92)	21.62 (6.50)	0.1512	0.1165

Coefficients are shown with t-statistics in parentheses, *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

The Bottom10% is characterized by higher transactional over-activation, which is the strongest contrast. At the same time, the Top10% displays higher market exposure, suggesting that reaching the top depends on maintaining sufficient participation in the market. By contrast, neither portfolio risk nor average transaction size significantly distinguishes the two groups. This suggests that access to the top depends on a selective balance between contained activity and adequate exposure, not simply on greater risk-taking or larger orders. Among individual characteristics, age is higher in the Top10%. Within OCEAN, Conscientiousness is higher in the Top10%, which is consistent with a self-control channel.

4.2 Distributional Reading of Ranking Positions

We move to a structural distributional reading of ranking positions using a Top25%, Middle50%, Bottom25% partition. This step assesses whether the variables that separate the extremes also structure ranking positions more gradually across the sample, or whether they reflect tail-specific contrasts.

Table 3. Quartile-Based Profiling: Top25% (n=33), Middle50% (n=67), Bottom25% (n=33)

Variable	**Top25% (Mean, SD)**	**Middle50 % (Mean, SD)**	**Bottom25 % (Mean, SD)**	**p Welch (3 groups)**	**p Kruskal–Wallis**	**p Welch (Top25 vs Bottom25)**	**p Mann–Whitney (Top25 vs Bottom25)**
Number of Transactions	13.03 (6.381)	17.78 (11.50)	27.36 (9.137)	1.265e-09***	8.762e-09***	7.029e-10***	5.586e-09***
Average cash holdings	0.5071 (0.1930)	0.6663 (0.2222)	0.5583 (0.1782)	0.001135***	0.001291***	0.2670	0.1177
Risk	2.021e+04 (8381)	1.585e+04 (7691)	2.009e+04 (4898)	0.002863***	0.008019***	0.9424	0.5552
Average Transaction Size	1.217e+04 (6840)	9669 (5825)	1.228e+04 (3955)	0.02618**	0.02522**	0.9339	0.7485
Age	22.61 (5.868)	20.31 (1.768)	20.39 (2.263)	0.1019	0.08591*	0.04984**	0.06418*
Gender (Male=1)	0.6364 (0.4885)	0.5075 (0.5037)	0.6667 (0.4787)	0.2439	0.2380	0.7999	0.8037
Openness	31.88 (5.424)	31.49 (5.577)	34.55 (5.333)	0.03045**	0.03869**	0.04824**	0.03907**
Conscientiousness	31.12 (6.333)	31.30 (5.919)	29.09 (5.276)	0.1559	0.2715	0.1621	0.2320
Extraversion	24.39 (5.820)	24.10 (6.073)	25.97 (5.587)	0.3049	0.3097	0.2661	0.3039
Agreeableness	38.88 (4.052)	37.99 (5.861)	38.39 (5.657)	0.6768	0.8830	0.6904	1.0000
Neuroticism	20.82 (6.555)	23.03 (6.587)	20.03 (6.152)	0.06458*	0.05355*	0.6164	0.8022

Coefficients are shown with t-statistics in parentheses, *** p < 0.01; ** p < 0.05; * p < 0.10

The quartile partition provides a first distributional reading of the ranking structure. Trading activity is the most discriminating dimension. It rises sharply from the Top25% to the Bottom25%, and the Top-vs.-Bottom contrast is large and significant. This extends the extreme-group evidence and suggests that over-activation is a structuring force of ranking positions. Cash holdings, risk, and average transaction size are significant in the global three-group tests, but the Top25% vs. Bottom25% contrast is not significant. These variables appear to differentiate some parts of the distribution rather than supporting a linear “top versus bottom” contrast. On the individual and psychological side, Openness is higher in the Bottom25% than in the Top25%, while the other OCEAN traits are less discriminating. Age shows a weak signal, whereas gender does not structure ranking positions.

4.3 Quantile Regressions: Extreme Quantiles

We examine conditional associations across performance distribution, starting with extreme quantiles, to identify mechanisms specific to the lower and upper tails.

Table 4. Quantile Regressions on Return

Variable	**q = 0.10**	**q = 0.90**
Constant	-0.00261819*** (-6.64)	0.00188845*** (5.11)
Activity (z)	-0.00262192*** (-10.00)	-0.000782863** (-2.05)
Cash holdings (z)	-0.00109262** (-2.36)	-0.00164004*** (-5.41)
Risk (z)	0.000407836 (0.90)	-0.000478648 (-1.35)
Average transaction size (z)	-0.00164294*** (-5.11)	-3.46847e-05 (-0.08)
Age (z)	0.000432724** (2.12)	0.000491421 (1.64)
Openness (z)	-0.000612523** (-2.51)	-0.000386864 (-1.53)
Conscientiousness (z)	-7.04607e-05 (-0.29)	-0.000235469 (-0.93)
Extraversion (z)	9.32577e-05 (0.61)	-0.000274566 (-1.16)
Agreeableness (z)	-3.95254e-05 (-0.15)	-4.19022e-05 (-0.16)
Neuroticism (z)	2.02874e-05 (0.08)	-3.17497e-05 (-0.11)
Gender (Male=1/Female=0)	-0.000920592 (-1.63)	-0.000813628 (-1.49)

Coefficients are shown with t-statistics in parentheses, *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Pseudo R^2(Koenker–Machado R1) = 0.479 at q = 0.10 and 0.281 at q = 0.90.

The extreme-quantile results confirm an asymmetry in ranking mechanisms in our design. At the lower tail, activity remains strongly negative and highly significant, reinforcing the interpretation of costly over-activation: among lower-tail outcomes, “doing more” is associated with weaker performance. Average transaction size is also negative and significant at q = 0.10, suggesting that strong underperformance is also linked to decision intensity. Cash holdings variable is negative and significant at q = 0.10, indicating that under-exposure limits the ability to recover even in the lower tail. By contrast, risk does not emerge as a robust determinant.

At the upper tail, the structure changes. Activity remains negative and significant, but with a smaller magnitude, suggesting that over-activity is still unfavorable even for high-ranking outcomes, but is not the dominant mechanism of top-tail access. The strongest signal concerns cash holdings variable, which is negative and significant at q = 0.90. Remaining too liquid appears to limit access to top-ranking positions. In contrast, average transaction size is no longer discriminating, which is consistent with a profile driven more by exposure and selectivity than by order size.

On the individual and psychological side, the picture is nuanced. At q = 0.10, age is positive and significant, suggesting that relatively older participants tend to perform less poorly within the lower tail of the performance distribution. Also at q = 0.10, Openness is negative and significant, indicating that a more exploratory style may be associated with greater vulnerability in the worst performance ranks. The other OCEAN dimensions and gender do not show effects in the extreme-quantile specification.

4.4 Quantile Regressions: Central Quantiles

We examine the central quantiles to assess whether the mechanisms observed in the tails also structure the core of the performance distribution, or whether they are primarily tail-specific.

Table 5. Quantile Regressions on Return

Variable	**q = 0.25**	**q = 0.50**	**q = 0.75**
Constant	-0.00215497*** (-6.05)	-0.000857999** (-2.54)	0.000234752 (0.668)
Activity (z)	-0.00239082*** (-10.7)	-0.00142618*** (-6.44)	-0.00114893*** (-4.15)
Cash Holdings (z)	-0.000957343** (-2.39)	-0.000776442** (-2.29)	-0.0012919*** (-3.79)
Risk (z)	0.000338424 (0.919)	0.000177012 (0.543)	-0.00033651 (-0.843)
Average Transaction Size (z)	-0.00170714*** (-5.98)	-0.00106905*** (-3.67)	-0.000659325* (-1.81)
Age (z)	0.000377313* (1.71)	0.000346064 (1.64)	0.000278828 (1.51)
Openness (z)	-0.000166685 (-0.733)	-0.000173581 (-0.819)	-0.000241786 (-1.06)
Conscientiousness (z)	-9.77649e-05 (-0.438)	-4.86472e-05 (-0.226)	0.000279165 (1.09)
Extraversion (z)	-0.000152416 (-0.809)	-3.03029e-05 (-0.156)	0.000131103 (0.591)
Agreeableness (z)	-5.45117e-06 (-0.0253)	0.000134132 (0.619)	-8.23701e-05 (-0.344)
Neuroticism (z)	0.000238229 (1.17)	0.000105322 (0.494)	5.49836e-05 (0.227)
Gender (Male=1)	-0.000546743 (-1.04)	-7.93296e-05 (-0.163)	-0.000142537 (-0.291)

Coefficients are shown with t-statistics in parentheses, *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Pseudo R^2(Koenker–Machado R1) = 0.394 at q = 0.25, 0.261 at q = 0.50, and 0.221 at q = 0.75.

The central-quantile estimates confirm the patterns identified in the 25/50/25 partition. Activity remains negative and significant from q = 0.25 to q = 0.75, indicating that “doing more” is systematically associated with lower performance across the core of the distribution. Cash holdings variable is also negative and significant across all three quantiles, suggesting that insufficient exposure penalizes performance in the middle of the distribution ranking. Average transaction size is negative and significant at q = 0.25 and q = 0.50, then becomes only marginal at q = 0.75, suggesting an effect strongly tied to underperformance and intermediate performance than to the upper part of the distribution. Risk is not discriminating once the other variables are controlled. For the individual and psychological variables, the signal remains limited in the central quantiles. Age is positively associated with performance at q = 0.25, while the OCEAN traits remain non-significant across the quantiles. Overall, the explanation of the rank remains primarily behavioral, with only a secondary contribution from individual characteristics.

4.5 Final Profiling Synthesis: Integrated Analysis Across Groups and Quantiles

The results support an interpretation consistent with the logic of a tournament. The quartile partition first reveals a structure in which trading activity is associated with ranking position, with a gradient from the top to the bottom of the distribution. This result is confirmed by the central quantile regressions, where the effect of activity remains negative and significant across the central part of the distribution.

A second structuring axis is market exposure. Across both central and extreme quantiles, cash holdings variable is negative and significant, indicating that under-exposure penalizes performance across performance segments. This relation becomes especially meaningful in extreme quantiles. In the lower tail, remaining in cash limits the ability to recover, whereas in the upper tail it is associated with reduced access to the best positions.

The Top10% vs. Bottom10% comparison and the extreme quantile regressions show that over-activity is especially costly in the lower tail, while average transaction size is mainly penalizing in the lower and central parts of the distribution, before weakening at q = 0.75 and becoming non-discriminating at q = 0.90. This pattern suggests that underperformance is associated with a combination of high decision frequency and imperfect calibration, whereas access to the top of the ranking depends more on contained activity and effective market exposure.

Portfolio risk does not emerge as a monotonic determinant in the quantile regressions, despite some descriptive differences across group partitions. This suggests that risk should be interpreted as a marker of portfolio configurations in certain segments of the distribution rather than as a linear predictor of success.

The evidence on individual and psychological variables is nuanced. In the Top10% vs. Bottom10% comparison, Conscientiousness remains higher among the Top10%, which is consistent with a self-control channel. However, this relation is not confirmed in the extreme quantile regressions, where Conscientiousness does not appear as a robust predictor. By contrast, the quantile models show lower-tail statistical signals for age and Openness.

Table 6. Summary of Hypothesis Testing

Hypothesis	Prediction	Empirical Evidence	Assessment	Comment
H1 Over-activation and Rank Underperformance	Higher trading activity is associated with lower relative performance	Top10 vs Bottom10, 25/50/25 partition, central and extreme quantile regressions	Supported	Strongest and most consistent result
H2 Exposure (cash holdings) and Access to the Top	Under-exposure is associated with lower relative performance, especially in the upper tail	Group comparisons, central quantiles, extreme quantiles (q=.90)	Supported	Negative across central and extreme quantiles; especially informative for top-rank access
H3 Risk as a Tail Marker rather than Monotonic Determinant	Portfolio risk is more likely to mark extremes than to predict rank monotonically	Quartile comparisons, quantile regressions	Partially supported	Some descriptive group differences, but no robust monotonic quantile effect
H4 Tail-Specific Mechanisms	Activity more informative in lower tail; cash more informative in upper tail	Extreme quantile regressions (q=.10/.90)	Supported	Lower-tail entrenchment pattern for activity; upper-tail access mechanism for exposure
H5 Personality Traits and Demographic Characteristics	Individual differences are expected to show segment-specific rather than uniform effects across the distribution	Top/Bottom contrasts, quartiles, quantile regressions	Partially supported (localized evidence)	Conscientiousness differentiates Top10% vs. Bottom10%; age and Openness show lower-tail signals (q = 0.10); no uniform effects for OCEAN traits or gender across quantiles

5. Discussion

Our results should be interpreted considering the design: a tournament-type incentive structure shifts participants' objective from maximizing average performance to improving relative performance. Tournament theory predicts that agents adjust their behavior according to their position and the rewards (Lazear & Rosen, 1981). In asset management, both theoretical and empirical evidence shows that rank-based incentives encourage strategic adjustments (Brown et al., 1996; Chevalier & Ellison, 1997; Basak et al., 2007). What matters is access to upper-ranking zones and the ability to escape lower-ranking zones (Koenker & Bassett, 1978).

5.1 Over-Activation: A Rank-Degrading Mechanism Consistent With Overtrading and Action Bias

The most robust result is the negative effect of trading activity. It appears clearly in the 25/50/25 partition, remains stable in the central quantiles, and persists in the extreme quantiles, with large magnitude in the lower tail. Lower-ranked participants are much more active than higher-ranked participants (Odean, 1999; Barber & Odean, 2000; Daniel et al., 1998).

This pattern is also compatible with overconfidence mechanisms, which increase action frequency and reduce returns (Gervais & Odean, 2001; Glaser & Weber, 2007). In a tournament context, however, the interpretation should be refined: over-activity may reflect catch-up behavior resulting from ranking feedback when participants recognize that they are falling behind. This dynamic resembles "chasing" behavior observed in relative-performance contexts (Brown et al., 1996; Chevalier & Ellison, 1997). The strength of the signal at q = 0.10 is suggestive of an "entrenchment" mechanism: the further participants are in the lower ranks, the more the urge to "do something" may translate into costly activity.

Decision psychology also helps explain why activity may increase when it is not productive. Reactions to feedback may also be driven by reference dependence and loss aversion: when portfolio outcomes fall below a reference point, individuals may adopt more aggressive strategies, consistent with prospect theory (Kahneman & Tversky, 1979). In addition, the literature on regret suggests that action may be chosen to reduce anticipated regret (Tykocinski & Pittman, 1998).

5.2 Market Exposure: A Cross-Cutting Mechanism

A second major result concerns market exposure. Contrary to an interpretation that would treat cash primarily as defensive prudence, cash holdings variable is negative and significant in both the central quantiles and the extreme quantiles. Under-exposure penalizes performance in the tails and in the core of the distribution. The asymmetry remains especially visible at the top: at the upper quantile, the cash signal is particularly strong. To reach the best positions, participants must maintain sufficient exposure to generate a performance differential. Remaining too liquid may reduce variance and the probability of outperformance.

Access to the top depends on a combination of contained activity and sufficient exposure. Relative underperformance can arise through overtrading and excessive under-exposure (Barberis et al., 1998; Hong & Stein, 1999). In other words, a poorly ranked investor may be someone who trades frequently while remaining insufficiently exposed.

The fact that risk does not emerge as a monotonic determinant in quantile regressions reinforces this interpretation. Volatility does not appear to function as a one-directional driver of rank. This is consistent with approaches emphasizing heterogeneous behavior (De Long et al., 1990; Lo, 2004). Some risky styles may result in very high or very low outcomes without producing a linear risk–performance relation. In a tournament, variance can increase the probability of "big wins" as much as "big losses," (Koenker & Bassett, 1978).

These patterns about exposure and activity are consistent with a lower-performing behavioral configuration in which students multiply trades while remaining under-exposed. In a novice learning context, this may reflect cautious sizing and uncertainty about firms or market functioning, though these underlying mechanisms are interpretive.

5.3 OCEAN and Individual Characteristics: Localized Moderators Rather Than a Psychological Driver

Adding OCEAN traits and individual characteristics clarifies why some responses to tournament pressure may be more likely for some individuals. From a differential psychology perspective, traits do not determine performance but they modulate the probability of adopting certain behaviors (Mischel, 1968; John & Srivastava, 1999; McCrae & Costa, 2008).

On the one hand, Conscientiousness remains informative in the Top10% vs. Bottom10% comparison: it is higher among Top10% participants, which is consistent with a role for self-control in distinguishing outcomes and with behavioral interpretations of self-control, where discipline operates as a self-regulation mechanism (Thaler & Shefrin, 1981; Shefrin, 2000). However, this signal is not confirmed in the quantile regressions.

On the other hand, the extreme quantiles highlight two signals. First, age is positive and significant at q = 0.10, suggesting that among underperforming situations, slightly older participants perform better. Second, Openness is negative and significant at q = 0.10, and the quartile partition also shows higher Openness in the lower quartile. A more exploratory style may increase vulnerability. This does not mean that Openness is inherently "bad," but its behavioral expression depends on execution constraints (McCrae & Costa, 2008; Durand et al., 2013; Mayfield et al., 2008).

The absence of results for Extraversion, Agreeableness, and Neuroticism confirms that personality does not operate as a dominant determinant. Psychological variables appear as localized moderators in some segments or in comparisons of extreme profiles.

5.4 Toward Data-Driven Profiling: Segmentation of Trading Styles

Our analyses reveal behavioral styles associated with ranking zones and show that these styles are expressed differently across positions in the performance distribution. This approach is consistent with segmentation literature (Wedel & Kamakura, 2000).

Based on the results, two "proto-profiles" remain visible:

- An under-exposed over-activation profile in the lower tail (high activity, high cash holdings, penalizing average transaction size);
- A selectively exposed profile in the upper tail (low cash holdings, contained activity, non-discriminating average transaction size at the top).

This result avoids over-psychologizing the tournament design and keeps the explanation grounded in behavioral variables.

Our variables are well suited to data-driven approaches such as clustering or mix models (Hastie et al., 2009; Jain, 2010; Aggarwal & Reddy, 2014; Collins & Lanza, 2010; Vermunt & Magidson, 2002; Lanza & Rhoades, 2013). This perspective is also consistent with the literature on heterogeneity among individual investors and that decision styles affect trading and performance (Dorn & Huberman, 2005; Grinblatt & Keloharju, 2009; Kumar, 2009; Barber & Odean, 2001). OCEAN can be treated as a complementary profiling level in explaining the relative stability of some response styles (John & Srivastava, 1999; McCrae & Costa, 2008).

Our results have direct implications for future design. If rankings and rewards shape student behavior, they should be considered as pedagogical mechanisms that require monitoring and debriefing. The next section translates these results into practical guidance for classroom implementation, focusing on what the ranking rule is doing behaviorally, which recurring student profiles instructors should expect, and how design debrief protocols can preserve the benefits of competition.

6. Teaching Implications for Trading Simulations

6.1 Translating the Empirical Profiling Into Teaching-Relevant Behavioral Configurations

To translate the empirical profiling into practice, the results can be reformulated into several teaching-relevant behavioral configurations. They represent behavioral patterns that may emerge under a specific design.

A first configuration, observed in the lower tail, can be described as a reactive under-exposed chasing pattern. This configuration combines high trading activity, high cash holdings and a penalizing average transaction size. This pattern is consistent with catch-up behavior under ranking pressure: students react to poor ranking by increasing decision frequency, but without maintaining the market exposure necessary to recover. The result is a costly loop in which activity increases while performance deteriorates.

A second configuration, observed in the upper tail, can be described as a selectively exposed pattern. This configuration is characterized by lower cash holdings and more contained trading activity, while average transaction size is not a discriminating feature. High-ranking performance depends on maintaining exposure while avoiding reactive overtrading.

The psychological variables add nuance but they do not replace the behavioral explanation. In the Top10% vs. Bottom10% comparison, Conscientiousness remains higher among top performers, which is consistent with a discipline channel. However, this pattern is not robust in the extreme-quantile regressions. By contrast, the lower-tail quantile results show localized signals for age and Openness, suggesting that some individual characteristics may shape vulnerability to lower-tail deterioration. For teaching purposes, instructors can target behavioral patterns (over-activation, under-exposure, reactive chasing) without treating personality traits as deterministic explanations.

Table 7. Teaching-Relevant Behavioral Configurations Under Tournament Ranking

Behavioral Configuration	**Empirical Signals**	**Tournament Interpretation**	**Teaching Implications**
Reactive Under-Exposed Chasing Pattern (lower tail; q = 0.10)	Over-activation, under-exposure); penalizing average transaction size in lower/lower-central quantiles; risk not discriminating; lower-tail moderation by age and Openness	Continuously visible rankings may result in reactive catch-up behavior: students trade more while remaining insufficiently exposed to recover.	Disrupt the catch-up loop: pacing rules, pre-trade checklists, trade-rationale prompts, calibration coaching on order size during losing phases, debriefs focused on rank-driven reactions.
Selectively Exposed Pattern (upper tail; q = 0.90)	Lower cash holdings; contained activity; average transaction size non-discriminating at the top; risk not robustly discriminating	Top performance is associated less with staying exposed while avoiding reactive responses to rank fluctuations. Selectivity supports persistence in high-ranking positions.	Reinforce disciplined selectivity: exposure checkpoints, no-trade justification routines, written decision rationales, training in tolerating disciplined inaction.

6.2 From Behavioral Configurations to Design Structured Supports

Building on those teaching-relevant behavioral configurations, the next instructional step is to identify design guardrails that can reduce behavioral drift without eliminating the value of competition. The core pedagogical implication of the profiling results is that the main risk in this tournament-style simulation is misdirected engagement: students may respond to rankings and performance pressure by increasing trading activity in ways that are reactive and insufficiently supported by market exposure. This makes debiasing-oriented instructional routines relevant (Thaler, 1999; Kahneman, 2011; Shefrin, 2000; Fischhoff, 1982; Arkes, 1991; Larrick, 2004).

The behavioral configurations identified also support a profiling logic for classroom intervention rather than a one-size-fits-all correction strategy. Teachers can anticipate recurring response patterns under tournament conditions and align their instructional supports accordingly. This perspective is consistent with distributional profiling (Koenker & Bassett, 1978), segmentation logic in behavioral research (Wedel & Kamakura, 2000) and a cautious interpretation of personality (Mischel, 1968; John & Srivastava, 1999; McCrae & Costa, 2008). In our results, Conscientiousness remains informative in extreme-group contrasts, whereas age and Openness appear more locally in lower-tail (Thaler & Shefrin, 1981; Shefrin, 2000; Durand et al., 2013; Mayfield et al., 2008, Wedel & Kamakura, 2000; Jain, 2010; Collins & Lanza, 2010).

Five design teaching supports follow from the empirical patterns and are intended to improve process quality under competitive pressure:

- Pacing rule: limit rapid repeated execution under rank pressure (e.g., trade budget by time block or a mandatory pause before consecutive trades) to reduce action bias and reactive chasing (Patt & Zeckhauser, 2000).
- Minimum time between trades: use a short interval as a behavioral circuit breaker to slow intuitive responses and reduce noise-driven reactions to rank fluctuations (Kahneman, 2011; Larrick, 2004).
- Written trade rationale: require brief justifications (signal, horizon, risk, exit condition), especially after rank declines, to shift attention from rank movement to process quality (Fanning & Gaba, 2007; Fink, 2013).
- Exposure checkpoint: periodically require students to report and justify their cash ratio, since under-exposure is a penalty across central and extreme quantiles; this also connects to portfolio teaching on exposure, diversification, and return–variance trade-offs (Markowitz, 1952).
- No-trade justification: occasionally require students to justify not trading, thereby legitimizing disciplined inaction (Thaler, 1999; Kahneman, 2011; Shefrin, 2000).

These mechanisms are consistent with debiasing approaches that combine bias awareness, structured feedback and decision procedures that slow rapid intuition (Fischhoff, 1982; Arkes, 1991; Larrick, 2004). They should be framed as learning support, so that students come to see them as tools for improving judgment under pressure rather than as constraints.

6.3 Debrief Protocol

Research on simulation-based training shows that learning gains depend on feedback (Kolb, 1984; Fanning & Gaba, 2007). Debriefing should focus on behavioral diagnostics.

A practical debrief can be organized around four comparisons. First, activity and performance make over-activation visible and supports discussion of overtrading, cost amplification, timing illusions and noise misinterpretation (Odean, 1999; Barber & Odean, 2000; Daniel et al., 1998; Gervais & Odean, 2001; Glaser & Weber, 2007). Second, cash exposure vs. performance helps replace “simplistic” lessons (“be bold”,“be cautious”) with calibrated exposure, while linking portfolio logic and the psychology of under-exposure (Markowitz, 1952; Kahneman & Tversky, 1979). Third, reconstructing reactive chasing sequences after rank deterioration makes catch-up dynamics and action bias observable (Brown et al., 1996; Chevalier & Ellison, 1997; Basak et al., 2007; Patt & Zeckhauser, 2000). Fourth, structured reflection questions (e.g., reasons behind recent trades, rank effects on time horizon, trading to improve expectation versus reduce discomfort, perceived safety of cash) could support self-regulation (Kolb, 1984; Fanning & Gaba, 2007; Kahneman, 2011; Shefrin, 2000). This debrief structure also helps teachers connect the empirical profiling logic to classroom learning goals by showing which behaviors are associated with performance and how their costs vary across positions in the ranking distribution.

6.4 How to Use Competition Without Over-Activating Students

Competition can increase attention, participation, and motivation, and it can make theories more operational (Deterding et al., 2011; Hamari et al., 2014, Finet et al., 2025). In a continuously ranked simulation, competitive energy can shift from productive engagement to reactive overtrading. Teachers can modulate tournament intensity and redesign feedback so that competition supports learning rather than anxiety (Lazear & Rosen, 1981; Brown et al., 1996; Basak et al., 2007).

Practical options include reducing ranking refresh frequency, combining rank-based rewards with process-quality criteria, penalizing excessive activity or rewarding discipline, integrating exposure calibration into evaluation and alternating competitive and reflective phases. These adjustments preserve motivational benefits and limit unproductive catch-up dynamics and help students develop stable decision processes (Lazear & Rosen, 1981; Brown et al., 1996; Basak et al., 2007).

The findings support a tournament pedagogy in finance education: students should learn about market behavior while also developing the ability to regulate their own behavior under performance pressure (Odean, 1999; Barber & Odean, 2000; Kahneman, 2011; Shefrin, 2000).

7. Conclusion

This study shows that a simulated trading environment organized as a tournament reveals performance differences. It also makes ranking dynamics visible. In this sense, the article’s main contribution is to shift the analysis from average performance to distributional performance by identifying the behavioral configurations associated with upward movement or decline in the ranking (Lazear & Rosen, 1981; Koenker & Bassett, 1978). In our competitive setting, extreme performance is explained by the combination of contained trading activity and sufficient market exposure, which is consistent with the literature on excessive trading (Barber & Odean, 2000).

The analytical approach also makes visible the asymmetrical mechanisms across ranking positions. The mechanisms associated with remaining in the lower ranks differ from those associated with reaching the top. Over-activity (in some segments, average transaction size) mainly penalizes the lower tail, whereas under-exposure emerges as a constraint on access to the highest positions.

Integrating OCEAN does not explain the ranking, and no trait emerges as a robust predictor across all models. Conscientiousness remains informative in the Top10% vs. Bottom10% comparison, which remains compatible with self-control interpretation. However, this effect is not confirmed in extreme quantile regressions. By contrast, the evidence for age and Openness is localized: Openness differentiates the Top25% vs. Bottom25% groups, whereas age appears in the lower-tail quantile results.

To answer the research question, the findings show that in our simulation, relative performance is shaped primarily by behavioral factors with distributional asymmetries across the ranking while individual and personality variables operate mostly as localized moderators rather than stable determinants, supporting a tournament approach to simulation design and debriefing in financial education.

8. Study Limitations

This study is based on an intraday educational simulation conducted with students, which strengthens control over the instructional setting while limiting direct extrapolation to experienced investors. However, our objective is not statistical generalization but to inform a design-oriented reflection on how trading simulations are structured, incentivized, and debriefed. The study is intended to generate pedagogical insight into behavioral responses under a specific simulation architecture, rather than to estimate universal effects.

A second limitation concerns the temporal scope of the exercise. The simulation is conducted within a short intraday session, which means the study captures immediate behavioral responses to ranking feedback and tournament incentives rather than stabilized learning trajectories. As a result, the findings are informative for the design of short-format simulations and less suited to drawing conclusions about behavioral adjustment across learning processes.

Third, several findings rely on comparisons between the top and bottom segments. This focus is consistent with tournament logic, but it implies lower statistical power, greater sensitivity to atypical observations and a more descriptive than structural interpretation of some contrasts. More broadly, the study combines multiple empirical perspectives (Welch tests, Mann–Whitney tests, quartile comparisons, and quantile regressions), which raises the issue of multiplicity. The most reliable signals recur across methods, whereas localized effects (e.g., some OCEAN traits or age effects) should be interpreted more cautiously.

Fourth, risk and average cash holdings capture dimensions of trading behavior, yet they do not fully represent the portfolio choices (e.g., concentration or timing of exposure). Similarly, trading activity aggregates heterogeneous decisions and average transaction size does not capture timing. According to the quantile results, these indicators are informative, but the underlying mechanisms are not identified (e.g., episodic chasing vs. persistent style differences).

Finally, personality is measured through self-reported OCEAN traits, which may be affected by social desirability. Personality is used as a profiling resource, not as a causal mechanism. More generally, the combined profiling and quantile strategy is designed to map patterned associations but not to identify causal effects.

9. Directions for Future Research

A first extension would be to manipulate the incentive structure to test behavioral sensitivity to tournament design (varying reward size, reward depth, or introducing a mixed reward scheme). It would allow a more direct identification of whether over-activation is a strategic response to ranking incentives or a stable behavioral tendency. Similarly, comparing a real-time visible ranking condition with hidden rankings would help isolate the effect of social feedback.

Second, an extension would exploit the temporal detail in the data: activity across subperiods, transitions into catch-up sequences and exposure-timing indicators. Such an approach would help test whether rank deterioration is driven by episodes of escalation rather than uniformly high activity, and whether access to the top depends on stable exposure or opportunistic risk-taking. This extension would be useful for deepening the mechanisms in extreme quantiles.

Third, the data-driven profiling axis could become a standalone empirical contribution: constructing behavioral segments based on activity, cash holdings, average transaction size, risk, and then linking these segments to final rank. The current results already provide “proto-profiles”, which formal segmentation could consolidate.

Fourth, a psychological extension would involve measures close to action regulation under pressure (impulsiveness, self-control, and sensation seeking). This would help understand why some participants shift toward unproductive strategies.

Fifth, external robustness should be tested through replications across other populations (retail investors, professionals), other markets/assets (U.S. equities, indices) and other durations to observe learning and the stabilization of trading styles. Multi-session replications would be useful for assessing whether the“winning” configuration is a stable pattern or a session-contingent outcome.

Finally, a direction would be to test instructional interventions: pre-commitment tools, structured feedback, activity constraints or written order-justification rules. The goal would be to assess whether these devices reduce over-activation, improve effective market exposure and alter the distribution of ranks. This would turn the study into a more complete framework able to assess pedagogical design mechanisms that can improve learning and limit behavioral drift.

Authors' contributions

Conceptualization, A.F.; investigation, A.F., K.K., and J.L.; resources, K.K. and J.L.; data curation, K.K. and J.L.; writing—original draft preparation, A.F., K.K., and J.L.; writing—review and editing, A.F., K.K., and J.L.; supervision, A.F.; project administration, A.F.; funding acquisition, A.F. All authors have read and agreed to the published version of the manuscript.

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Appendix: Big Five (OCEAN)

Participants’ personality is assessed using the Big Five Inventory developed by John et al. (1991) and validated by Plaisant et al. (2010). The questionnaire comprises 45 items presented as short statements measuring the five major personality dimensions, namely Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. For each statement, participants indicate their level of agreement on a five-point Likert scale, where 1 corresponds to “strongly disagree” and 5 corresponds to “strongly agree.” Personality scores are computed as the mean of the items included in each dimension. The full set of items is not reproduced here because the questionnaire is subject to copyright restrictions.

Extraversion comprises eight items. Agreeableness comprises ten items. Conscientiousness comprises nine items. Neuroticism comprises eight items. Finally, Openness comprises ten items. Each of the five dimensions is therefore computed as the mean across its items, with reverse-scored items recoded prior to aggregation.