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ORIGINAL RESEARCH

Measuring contextuality in investment preferences

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Abstract
This study investigates the role of contextuality in investment preference formation, specifically in global investments and major US stocks. Utilizing the "Contextuality by Default" framework (Dzhafarov and Kujala in PLoS ONE 8:e61712, 2013; J Math Psychol 74:11–33, 2016), we measure contextuality within a cyclic system of random variables. Through two experiments, each with four context stimuli, we assess contextuality across various decision-making scenarios. Our results indicate the presence of "true" contextuality in global investment decisions, but not in US stock selections. We investigate the determinants of contextual preference formation, focusing on factors such as future return expectations, risk perception, and familiarity with stock markets and individual US stocks. Employing logistic regression analysis for the first two contexts, we find that preferences in foreign stock markets exhibit instability, indicating context-specific drivers. On the other hand, familiarity with individual companies and future return expectations consistently influence investment preferences in specific US stocks.

Keywords Behavioural finance · Contextuality by default · Experimental finance · Financial decisions · Framing

JEL Classification C90 · D8 · D81 · G11 · G41

1 Introduction

In behavioral finance and economics, preference reversals are largely explained through the lens of two major contextual factors: framing effects and order effects, which can profoundly affect agents' decision-making states. One of the central axioms of Expected Utility Theory is that preference should be description invariant, also known as context independence. That is, the way the options are presented should not influence people's choices. Starting with the seminal works by Tversky and Kahneman (1981), and Kahneman and Tversky (1984), the impact of framing effects on human choices was explored. Other studies documented that the decision frame can also encapsulate visual and audio stimuli, as well as people's internal

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frames, shaped by their personality, background, and emotions (Druckman & McDermott, 2008; Kühberger et al., 1999; Nabi et al., 2020). Framing effects are also immune to, for example, monetary stimulation with real payoffs (Kühberger et al., 2002). Furthermore, framing effects become more pronounced when decisions are made under time constraints, as shown by Guo et al. (2017).

Our work contributes to the literature on contextual behavior in the following ways:

We are proposing a more unified statistical measurement of preference contextuality in financial decision-making via the analysis of the experimental statistics with the aid of the CbD (Contextuality by Default) framework,[1] to mathematically quantify the "disturbance" that the various financial choice contexts create.

Simultaneously, we enhance the scenarios in which the contextuality emergence is examined. Secondly, we broaden the scope of existing studies that have measured the contextuality of random variables with the CbD model in more simulated settings. These settings include scenarios such as selecting features of heroes in a fairy tale story (Cervantes & Dzhafarov, 2018), choosing among combinations of meals and gifts (Basieva et al., 2019) and recently, making facial trait judgements (Bruza et al., 2023). We apply these methods to investment-related decisions, particularly focusing on real choices about stock market investments as part of portfolio creation.

To the best of our knowledge, our experimental studies represent the first attempt to measure contextual preferences in financial decision-making within the framework of the CbD model. Specifically, we assess the potential existence of contextuality (as defined by CbD) through two investment-related experiments. The first experiment addresses a macro-investment context, while the second focuses on domestic US investments, incorporating pairs of stocks from the DJIA index into a portfolio.

In the first study, participants engage with global investments, by choosing between portfolio allocations of foreign countries' index funds.[2] The investment decisions concern a selection of stock index funds from eight different countries presented across the contextual cyclic system. Countries for investments are selected from various geographic regions and are paired based on their 5-year historical stock market risk premiums, following the methodology outlined in Damodaran (2020). We follow up the experiment with a set of questions to elicit the potential drivers for the specific investment patterns across contexts. These factors include among others the perceptions of a region's risk, expectations of country index returns and risks, and the level of familiarity and information about the country's financial market.

In the second study, participants are instructed to pick stocks sampled from the Dow Jones Index (DJIA) and matched according to the company's sector, beta, and historical returns. Participants make choices about investing in eight shares presented in four investment (question) contexts.[3] We also elicit respondents' beliefs about the future performance of the stocks, familiarity with these stocks, and expectations about the overall US stock market performance in the future. After completion of both experiments, we administered a series of

[1] This is a modified framework of an equation used in quantum physics to observe the strengths of dependencies between quantum systems. CbD is developed by Dzhafarov (2003) and Dzhafarov and Kujala (2013, 2016) to quantify the statistical violations in cognitive data. We will provide a more formal background and definition of this framework in the next sections of the paper.

[2] From the perspective of US retail investors.

[3] We select four investment-choice contexts, corresponding to a contextual system of rank four that is the classical setup of CbD framework employed in earlier studies (Basieva, et al., 2019; Cervantes & Dzhafarov, 2018). The rank four system of measurements is also the most widely known form of the original, quantum physical Bell inequality tests, due to Clauser et al. (1969).

questions aimed at understanding their financial risk tolerance, financial literacy, investment experience, potential overconfidence, and cognitive reflection.

We designed the two experiments as macro and domestic investment scenarios, informed by prior studies indicating a more pronounced emergence of contextuality in less familiar and uncertain contexts (Busemeyer & Bruza, 2024; Haven & Khrennikova, 2018; Pothos et al., 2017; Schwarz, 2007; White et al., 2014). Additionally, research on familiarity and home bias suggests that investors exhibit stronger and more stable preferences for stocks and markets with which they are more familiar and knowledgeable (Ackert & Church, 2009; Ackert et al., 2005).

We recruited U.S.-based participants for our study via the M-Turk platform, and our sample size was 837 participants.

Our analysis, conducted within the framework of the Contextuality by Default (CbD) model, demonstrates that contextuality, extending beyond mere informational disturbance, is apparent in the initial experiment concerning global investments. However, this contextuality is absent in the experiment involving investments in stocks selected from the DJIA index, where only informational disturbance is observed.

We conduct a binary logistic regression for the first two contexts to identify potential influencing variables (e.g., return expectations, risk attitudes, and certain personal variables) and assess their stability across contexts. The results indicate that explanatory variables are unstable in the first experiment, while preferences for specific stocks in the second experiment remain relatively consistent and are primarily driven by familiarity and higher return expectations.

The remainder of the paper is organized as follows. In the next section, we survey the current state of research on contextual preferences, notably framing and order effects, with a focus on investment settings. We assess how models derived from quantum physical formalism have the potential to quantify such manifestations of preference reversals. In Sect. 3 we provide a more formal definition of the CbD framework. In Sect. 4 we detail our methodology and experimental design. In Sect. 5 we present the findings of our contextuality analysis. We conduct an additional analysis using binomial logistic regression to identify the main factors that could shape specific investment patterns and determine whether these factors differ between contexts. This analysis is performed for the first two contexts.

In Sect. 6 we stipulate a general discussion of the observed results and evaluate the possible influential factors of contextual investment preferences. In Sect. 7 we conclude and offer some recommendations and directions for further research on contextuality analysis in financial decision making.

2 Literature review

In the realm of financial decision-making, investment preferences can be significantly influenced by both external and internal frames of the decision-makers as demonstrated in the studies by Kumar and Lim (2008) and Ross and Simonson (1991). These frames, acting as cognitive lenses, can shape how decision-makers perceive and interpret information, thereby affecting their ultimate choices. Kumar and Lim (2008) associate narrow frame adoption in portfolio performance evaluation with less clustered trades giving rise to a disposition effect type behavior and portfolio under-diversification. De Martino et al. (2006) delve deeper into the neuro-psychological processes underpinning preference formation under negative and positive decision frames, showing that susceptibility to framing is jointly driven by personal characteristics and the exogenous environment. It can encompass a broader range of factors, including investors psychological state, market conditions, socio economic factors, and the intricate interplay of these elements.

Another enduring manifestation of contextuality, known as order effects, has been extensively explored in marketing research, opinion polls, and surveys (De Jong et al., 2012; Hogarth & Einhorn, 1992). The statistics of preference reversals, when questions, or more broadly random variables, are measured in a different order have been widely explained with the aid of frameworks of constructive processes (Atmaspacher & Romer, 2012; White et al., 2014). Decisions are not pre-stored in human cognition but are formed in the process of posing the question that acts akin to a "measurement" of the human cognitive system, thereby altering the subsequent decision outcomes.

The manifestation of order effects in financial settings has been examined in the context of investors' perceptions of a company's earnings announcements (Alexander & Ang, 1998; Frederickson & Zolotoy, 2016), as well as in evaluations of price charts featuring distinct sequences of negative and positive returns (Grosshans & Zeisberger, 2018).

Another explanation for preference reversals in joint versus separate representation of prospects (choices), as a form of exogenous framing, was proposed in the works by Hsee (1996) and Hsee et al. (1999). The "evaluability hypothesis," as formalized in these works, offers an attention-based explanation for preference reversals. It suggests that a joint representation of options reveals previously hidden salient feature "weights" that are assigned to the attributes of the prospects. However, in separate evaluations, an underweighting of these attributes occurs. This type of preference inconsistency can be documented as another manifestation of contextual preference formation. This contextuality phenomenon has a close link to the mathematical formalization of contextual preferences within the Contextuality by Default Theory (Dzhafarov, 2003; Dzhafarov & Kujala, 2013, 2016), which will be considered next. In the behavioral finance literature, there is ample evidence on how preference reversals occur. However, unified analyses of the deviations between observed statistical violations of choices and those predicted by classical probability theory (as postulated by Kolmogorov, 1950) remain limited. The CbD framework seeks to bridge this gap by mathematically quantifying the impact of contextual influences on decision-making statistics. To exemplify, in the Kolmogorovian set-theoretic approach, order effects would not naturally occur, as the joint distribution of independent random variables can always be attained. This means that the sequence of measurements does not alter their probability distributions. Mathematically, this suggests that for a pair of random variable questions (A, B) with dichotomous outcomes (+ /−), a joint probability can always be derived, such that, $p(A = +, B = -) = p(B = -, A = +)$. The presence of order effects, or "disturbance," induced by the question context can be viewed as a deviation from the axioms of classical probability that underpin neoclassical decision-making frameworks (Hogarth & Einhorn, 1992; Wang et al., 2014). The findings on the existence of order effects in various decision-making domains highlight the complex interplay between context and decision-making, challenging traditional models and calling for a more nuanced understanding of these processes.

In addition to extensive psychological research on these effects, an alternate body of literature in mathematical psychology and economics has sought to quantify their impact on human judgment and explain them through the lens of quantum measurement theory.

Research examining the contextuality of random variables through the CbD framework aims to connect traditional quantum theory with experimental studies in human cognition and decision-making. The core question these studies seek to address is: *Can the contextuality in decision-making statistics be captured with the aid of some (modified) models of* *classical probability theory, or is its manifestation too strong, necessitating other (more general) frameworks to depict its magnitude?* Another important question is how to quantify contextuality in decision-making statistics and identify any regularities in its emergence.

Some studies have approached contextuality in judgment and decision-making through genuine quantum physical formalism, while others have quantified its emergence as a violation of joint distributions based on classical probability theory. The first stance of behavioral research evaluates contextuality as a departure from ‘classicality’ with the aid of the foundational tests of (non) satisfaction of Bell’s inequality in various setting such as e.g., decision-making, visuals, semantics[4] (Aerts et al., 2000; Bruza et al., 2015; Conte et al., 2008; Khrennikov, 2000). Recent studies by Dzhafarov and Kujala (2013), Asano et al. (2014), as well as generalized probability models of order and disjunction effects in Wangand and Busemeyer (2013), Wang et al. (2014), Khrennikova (2014) formalize contextuality in various decision contexts, from voting behavior to investments, as a deviation from classical probabilistic reasoning. Gallus et al. (2023) document that correlations violating Bell’s inequalities can be observed in the timeseries of various SandP500 stocks, with certain industries exhibiting a more pronounced non-classical structure in stock return correlations. This is consistent with recent research in risk management (e.g., Grundke & Polle, 2012), which identifies specific patterns in the stochastic dependency structures between asset returns across different industries and time periods.

The violation of Bell’s inequalities indicates that significant connections exist between the states of a system, pointing to the non-separability of these states. In psychological language, it means that the interconnectedness between random variables within a system transcends the classical bound, whereby they form an inseparable ‘whole’ with each other in a given context. In this work, we do not delve into a deeper discussion of quantum mechanical interpretation of entanglement and the emerging non-locality. Instead, our research follows a different path that seeks to determine the level of non-decomposability in cognitive phenomena represented by systems of random variables formalized as part of the CbD framework due to Dzhafarov (2003), and subsequent developments in Dzhafarov and Kujala (2013, 2016, and 2017). This framework extends the quantum mechanical concept of contextuality from violations of the Bell’s inequality to psychological phenomena. Studies of contextuality are not straightforward for cognitive systems because disturbances, also known as *direct influences*, are difficult to experimentally control. The CbD approach provides an extension to the formalization of Bell’s inequality through the introduction of a parameter that distinguishes the effects of direct influences from the genuine (non-classical) contextuality.[5]

In contextuality analysis, we can quantify the relative weight of information-driven or causal disturbances across contexts and the remaining contribution of non-explainable contextuality. Put differently, the presence of non-classical contextuality implies an impossibility to model the outcomes of the variables (decision-making tasks) within a single probability space and points to the non-commutative nature of judgments. We will define the model for evaluating the presence of contextuality and the relative impact of direct influences in the next section.

Several behavioral studies have been conducted, many of which did not identify contextuality beyond the presence of direct influences. This observation is supported by the meta-analysis conducted by Dzhafarov et al. (2015). It is noteworthy that recent studies have

[4] Due to Bell (1964) and a generalization known as CHSH (Clauser, Horne, Shimony, Holt) inequality, named after its founders (Clauser et al., 1969).

[5] In quantum physics jargon, one would say that the correlations between particles (e.g., electrons) are non-local and cannot be explained via the causal impact of some preexisting hidden variables if genuine contextuality is present.

reported a significant presence of contextuality in psychological data. For instance, the studies conducted by Cervantes & Dzhafarov (2018, 2019), as well as the research by Basieva et al. (2019), have provided evidence for the existence of 'non-classical' contextuality in decision statistics. This suggests that while the presence of contextuality beyond direct influences may not be a universal phenomenon, it remains significant in specific decision-making contexts.

3 Theoretical framework

3.1 Contextuality by default model

We briefly present the setup of the CbD framework that aims to mathematically quantify contextuality as a *dissimilarity* of random variables. When the context changes, the variable measuring some property (such as a decision-making question, or an investment task) is replaced by another random variable measuring the same property. One can say that the "frame" of the other random variable alters the context of measurement for the first random variable and the two random variables form a non-separable "whole" (Basieva et al., 2019; Bruza et al., 2023). Thus, any single experiment occurs in its unique context, characterized by its distinctive set of random variables. As articulated by Basieva et al. (2019), the main problem for the classical probability framework is that the measurements of the random variables in different contexts become stochastically unrelated and no joint probability distribution of these measurements can be found. The difference between the two random variables that measure the same property in different contexts can be found by evaluating their maximal coupling, as formalized in Dzhafarov and Kujala (2013). CbD serves as a generalization of the original Bell inequality that can be applied to any cyclic system of random variables with dichotomous realizations.

Following the formalization by Dzhafarov and Kujala (2016), we hypothesize that a given context may affect the probability distribution of outcomes associated with a question or decision-making task, thereby changing the identity of the random variable. More generally, a random variable R_q^c is given by its content (q) and context (c). Following Basieva et al. (2019), the content of the random variable can be a specific question with dichotomous outcomes.[6] When measuring two random variables jointly, we create a *question context*. To measure the deviation from the joint distribution across some random variables, the system of pairwise measurements of these random variables should be cyclical since the last context contains a joint measurement of questions q_n and q_1.

For a system of some rank, R_n, we expect the joint probabilities of the pairwise measurements of q_n questions in c_n contexts to satisfy the following probabilistic bounds (inequality) to be considered as *non-contextual*.[7] This is formalized mathematically in Eq. (1) and illustrated in Fig. 1**.**

We denote a random variable for the outcomes of the question q_i by the symbol, R_{q_i}. Then, for expected values of their joint measurement across n contexts, we get:

$$E\left[R_{q_1}R_{q_2}\right] + E[R_{q_2}R_{q_3}] + \ldots E[R_{q_{n-1}}R_{q_n}] - E[R_{q_n}R_{q_1}] \leq n-2 \tag{1}$$

[6] Analysis of random variables with more outcomes is also possible, see Cervantes and Dzhafarov (2019).

[7] We allude to the joint probability distributions of the above random variables measured in different contexts, forming a *contextual system* as depicted in Fig. 1. We omit the 'conjunction' sign for simplicity.

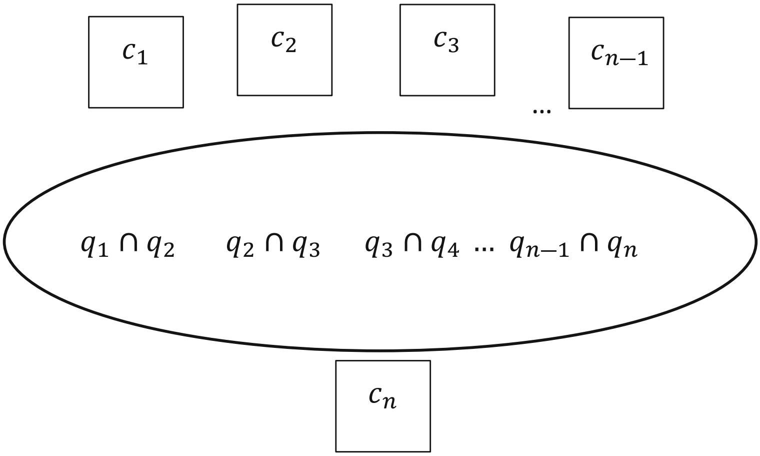


Fig. 1 Pairwise measurements in a cyclic system of rank N

For a R_4 system, widely explored in experimental settings (Basieva et al., 2019; Cervantes & Dzhafarov, 2018), the required inequality for the system to be *non-contextual* is:

$$E\left[R_{q_1}R_{q_2}\right]+E\left[R_{q_2}R_{q_3}\right]+E\left[\mathrm{R}_{q_3}\mathrm{R}_{q_4}\right]-E[\mathrm{R}_{q_4}\mathrm{R}_{q_1}]\le 2 \quad (2)$$

As noted, another important feature of CbD theory is that it separates between contextual influences of a direct, *casual* nature (i.e., some news that changes the choice outcome or the direct impact of the other jointly measured variable) and a *true* contextuality (i.e., no new information, or disturbance of a decision-making state) as firstly discussed in Dzhafarov (2003). When accounting for the possible impact of direct influences the inequalities in Eqs. (1–2) would be modified to include the so-called "delta" term."Delta" (Δ) captures the contribution to the presence of contextuality of the direct influences due to, e.g., informational disturbance. Since cognitive systems cannot be fully isolated from internal and external disturbances, (in contrary to experiments on genuine quantum systems), some presence of direct influences will be detected in cognitive experiments.

$$E\left[R_{q_1}R_{q_2}\right]+E\left[R_{q_2}R_{q_3}\right]+\ldots E\left[R_{q_n-1}R_{q_n}\right]-E\left[R_{q_n}R_{q_1}\right]-\Delta\le n-2 \quad (3)$$

To compute the maximum coupling in a rank N cyclic system and account for the effect of direct influences, we can define a function D as the difference between the S_{odd} function and the direct influences term. Following the definition of question-random variables in Eqs. (1–3), the functions S_{odd} and Δ can be defined through the expected values of random variables across each measurement context, e.g., $E\left[R_1^1R_2^1\right]$ denoting the expected value of c_1 measurement. We also reverse the inequality if we would like to observe the presence of genuine contextuality:

$$D=S_{odd}\left(E\left[R_1^1R_2^1\right]\right),E[R_2^2R_3^2],..,E[R_n^nR_1^n])-(n-2)-\Delta>0 \quad (4)$$

As mentioned, the main contribution of CbD to the original CHSH inequality is the consideration of the impact of informational disturbance (also called "direct influences" or "signalling) that can be interpreted as causal impact of cross-influence of the jointly measured random variables, plus other possible factors such as memory, and the external frame. Mathematically, the term Δ ("delta") measures the *differences* between the response frequencies to the same question across n contexts. It is given as:

$$\Delta = \left|E\left[R_1^1\right] - E\left[R_1^n\right]\right| + \left|E\left[R_2^1\right] - E\left[R_2^2\right]\right| +, .., \left|E\left[R_n^{n-1}\right] - E\left[R_n^n\right]\right| \tag{5}$$

Since we only considered R_4 cyclic systems in our studies (the most widely analysed system following the original CHSH inequality from quantum physics) we define following special form of the S_{odd} function following Basieva et al. (2019):

$$D = S_{odd}\left(\left[R_1^1 R_2^1\right], E\left[R_2^2 R_3^2\right], E\left[R_3^3 R_4^3\right], E\left[R_4^4 R_1^4\right]\right) - (4-2) - \Delta > 0 \tag{6}$$

For four contexts we compute S_{odd} as the maximum real number over the following combinations of correlations between 4 contextual measurements where the number of minus signs appearing should be odd (in this case either 1 or 3 times), $S_{odd} = \max |[\pm c_1 \pm c_2 \pm c_3 \pm c_4]|$. We note that to obtain this maximal coupling, i.e., $S_{odd}(1{,}1, 1, -1) = 4$, one needs to have one contextual measurement with the opposite correlation sign to the other three contextual measurements for R_4 cyclic system.

Similarly, Δ is given by:

$$\Delta = \left|E\left[R_1^1\right] - E\left[R_1^4\right]\right| + \left|E\left[R_2^1\right] - E\left[R_2^2\right]\right| + \left|E\left[R_3^2\right] - E\left[R_3^3\right]\right| + \left|E\left[R_4^3\right] - E\left[R_4^4\right]\right| \tag{7}$$

Online Appendix 1 (Eqs. A1.1—A1.4) details the computations of the cyclic combination of correlations between the expected values of dichotomous variables across the four contexts.

These computations determine the maximum value of the previously defined S_{odd} function.

3.2 An overview of different cyclic systems studied in recent experiments

Following the tradition of previous studies of contextuality analysis we depict below the "content-context" matrix for a system,R_4.

In the system from Table 1, we have 4 such pairwise measurements, where each measurement is denoted as *question context*, i.e., $c_1..c_4$.

Recent experiments of contextuality by Cervantes and Dzhafarov (2018) and Basieva et al. (2019) explored the systems of ranks R_3 and R_4, the latter, displayed in Table 1. One can surely generalize such a system to a $Q_i \times C_j$ matrix, where the mathematics will become more complex as one would need to compute the maximal couplings for exponentially many contextual outcomes. Another issue pertains to the violation of the assumption of *consistent*

Table 1 General setup of a contextual system

R_1^1	R_2^1			c_1
	R_2^2	R_3^2		c_2
		R_3^3	R_4^3	c_3
R_1^4			R_4^4	c_4
$q1$	$q2$	$q3$	$q4$	System ε(R_4)

Table 1 presents the context- content matrix for contextual measurements of rank-4 system ($R_{4)}$

connectedness within the system. As the complexity of the system grows, direct influences naturally emerge due to the increased level of information noise.

3.3 *Order effects and R_2 systems*

Order effects related to two questions asked in different order as well as joint evaluation of choice problems can be depicted as a rank two (R_2) contextual system. This is the simplest form of a system of random variables. Order effects can emerge within preference formation, judgments, and impressions (Khrennikova, 2014; Pothos et al., 2017; Wang & Busemeyer, 2013; White et al., 2014). The presence of order effects has been widely attributed to the constructive processes in our cognition, when preferences are not pre-recorded in our memory but constructed in the process of e.g., asking a question, deciding about investments, or forming more general preferences about matters (see also Kahneman & Snell, 1992).[8] Against this backdrop, Einhorn and Hogarth (1981) also speak of a so-called "problem space", which relates to different possible cognitive representations of the same decision-making tasks that would yield a different perception of the problem.[9]

Another example of a frame is the joint versus separate evaluation of objects or alternatives, as formalized in the evaluability hypothesis by Hsee (1996) and Hsee et al. (1999). These contextual preferences between joint and case-by-case evaluations are explained through attention shifting. The 'weights' placed on various attributes in terms of desirability are different in case-by-case and simultaneous evaluation settings. Notably, in joint evaluation lower weights might be attached to the same attributes that could be due to informational disturbance or a negative interference of preferences for these attributes (Dzhafarov, 2003; Haven & Khrennikova, 2018; Wang et al., 2014). Such an interference has been also observed in time-separated judgements, as demonstrated by Waddup et al. (2023), where memory can serve as an additional information channel, establishing a *"recollection as a correlation between queries at present and memories for past events"* (p.1952).

Within the realm of financial decision-making, CbD theory can serve as a unifying framework for understanding and quantifying the sources of contextual preferences in portfolio construction and diversification choices. Evaluating investment preferences within the framework of CbD could offer new insights into investor behavior and, consequently, improve portfolio management strategies.

4 Methodology

To enrich the findings on contextuality in the stock investment domain we devised two experiments, focused on global investments and domestic US investments. The first experiment pertained to the allocation of funds in global stock index funds. The second experiment examined the implications of integrating stocks from the Dow Jones Industrial Index into a well-diversified portfolio of U.S. stocks.

[8] In the R_2 system, only two contexts (c_1, c_2) are created by the order in which the random variables are measured. As noted by Cervantes and Dzhafarov (2019), the choice of a sequential measurement, versus a joint measurement of the two random variables doesn't affect the results within CbD analysis.

[9] The sequence and framing of information (or questions) can significantly influence an individual's perception and interpretation. The frame can be external (how the questions are presented) or internal (the cognitive frames of the decision-maker), which can sometimes be incompatible for different questions and decisions.

We utilized a cyclic system of rank four R_4, corresponding to pairwise choices between eight country index fund investments and eight pairwise stock selections from a major US stock index. We maintained four contexts to align our setup with previous studies on contextuality. The R_4 cyclic system represents a more general case compared to the simplest system of rank two. Basieva et al. (2019) employed R_3 and R_4 designs in their experiments, while Bruza et al. (2023) recently investigated R_3 systems. We considered, R_4, the highest rank system used to date, allowing for the collection of more comprehensive contextual statistics for CbD analysis.[10]

4.1 Method and participants

Participants for our study were recruited via the M-Turk platform. Previous studies have demonstrated that this platform provides a good balance between data quality and access to target respondents, thereby enabling us to target the U.S. population (Goodman et al., 2013; Kees et al., 2017). We approached participants from the U.S. due to the specific financial decisions they were required to make. The information sheet detailed that this would be an investment study, thus potentially attracting participants with investment experience or interest, who might find participation more engaging.[11] Participants were approached on April 1st, 2022, and paid for completed experimental surveys a remuneration of $2.5 for the between-group participation.[12] The experimental survey took, on average, 9–10 min to complete. The number of fully completed surveys was 837, with an average of 209 observations per experimental context. We aimed to collect at least 200 responses per context-treatment to attain a Cohen's d effect size of 0.3 with a standard power of 80% and an alpha level of 5%. The average age of the participants was 40 years, with 58% identifying as male and 81% indicating that they currently invest in financial instruments.

Table 2 provides a summary of the demographic and personal characteristics of participants:

4.2 Experimental design and procedure

As mentioned, we designed 2 experiments with 4 context—treatments in each. Each participant was randomly allocated into one of the 4 treatments in each experiment in the between-group design. In both designs, participants were presented with experiment 1 and experiment 2. We employed the setup of four contexts in our experiments following the design of experiments 5–6 in the meta-study of Basieva et al. (2019). This involved the introduction of a cyclic system rank four, resulting in a total of eight measurements of question-random variables about investment options.[13]

At the beginning of the experiments, all participants were presented with a study information sheet and informed consent form as well as given two attention check questions. We outline the experimental setup for experiments 1–2, with the experimental flow summarized in Table 3.

[10] This corresponds to tests of the original CHSH inequality, adjusted for direct influences.

[11] We also used the following filters, when recruiting the participants: (1) US as geographical location; (2) 95% approval rate, (3) minimum of 100 completed tasks.

[12] The survey was distributed on Friday afternoon.

[13] To mitigate possible order effects from the presentation format, we implemented a random sequence of presentations across the four conditions.

Table 2 Main characteristics of the sample

Sample	Between subjects (N = 837)
Gender	58% (m), 42% (f)
Average age	40 (st. dev., 12.4)
Current ownership of stocks/other financial instruments	81%
Trading experience (longer than 1 year)	88% (of those, who current own fin. assets)
Annual household income range for majority of participants	25% \$45,000–65,000 16% \$95,000 +
"I consider myself to be above average investor."	71%

Other notes:
97% of participants confirmed that they understood the questions of the study well
70% of participants have studied finance or business at the university level, with 28% of them also holding a Master's, MBA, or PhD
100% of participants confirmed that they currently reside in the U.S

Table 3 Experimental flow

Experiment 1 "Choosing between countries' stock markets in a global investment setting".	**Experiment 2** "Choosing stocks to add to a well- diversified portfolio of US stocks."	Financial literacy questions (8 questions), CR questions (3 questions), self-reported risk- taking, gender, age, trading experience, investments knowledge.

Table 3 displays the setup of our experimental design consisting of 2 blocks (experiments 1 and 2) and additional questions related to financial literacy, trading experience, cognitive reflection, personal and demographic characteristics. Please consult Online Appendix 6 for highlights of survey questions

4.2.1 Experiment 1: Foreign country investments: selecting countries' stock index funds

Participants in each investment context were asked to imagine that they are playing the role of a portfolio manager by managing a well-diversified portfolio of US stocks (mimicking the major US index) on behalf of a client. They were next asked to allocate a small fraction of funds into portfolios of major country stock index funds. Participants were presented with instructions and asked to confirm that they had read and understood these instructions.

In our study, we adopted a 'preparation' procedure following the study of Basieva et al. (2019) intending to guide participants to simultaneously select country stock index funds that carry relatively high and low risk as measured by the countries' equity risk premiums. For each condition (context), participants were presented with two possible scenarios in a random order: investing in a pair of high-risk and low-risk financial assets or investing in two high/low-risk assets simultaneously. For the cyclic system design of maximal correlations, we used the ($\pm$) investments statistics in the contexts 1–3, and (+ +) or (− −) statistics in c_4.

Before presenting the participants with specific country investment options, it was important to ensure that they were engaging with a setting that closely mirrored a realistic investment

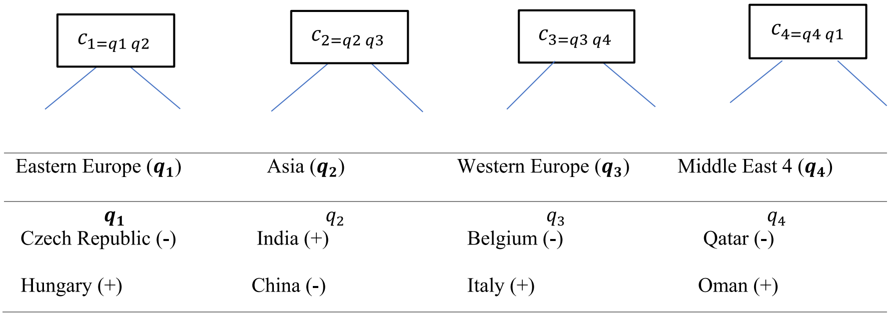


Fig. 2 Content-context matrix experiment 1

environment. Given that our participants were based in the United States, we utilized it as the benchmark country for evaluating the investment risk and return expectations associated with other countries' financial markets.

Experiment 1: data sampling and experimental procedure The relative risk associated with investing in country stock index funds was determined by the stock market risk premiums of these countries. Using the dataset and methodology of Damodaran (2020), we computed the risk premiums for a variety of countries and regions.[14]

To promote diversification, regions were presented in pairs, consisting of relatively high and low-risk regions. The same approach was applied to the investment funds of the two countries within each region. The selection of the choice sets in each context was based on the ranking derived from the average of the countries' default and equity risk premiums. In terms of risk premium computation and country selection, we collected equity risk premiums for various geographic regions as classified in Damodaran's dataset, please consult Online Appendix 2. After compiling the regional equity risk premiums for the years 2016–2020, we ranked the nine regions based on the average 5-year risk premium. Regions with the highest equity risk premium were subsequently excluded from consideration. This approach ensures a balanced representation of risk across the investment options presented to participants. In each investment context, participants were presented with a dichotomous choice between two countries, one from each region. A pairing strategy, inspired by the methodology of Kilka and Weber (2000), was implemented for the investment countries within each region, to ensure that the paired countries within each region exhibited similar investment profiles and economic scales.

Content—context matrix Following the experimental setups in Dzhafarov and Kujala (2016), and Basieva et al. (2019), we present a content-context matrix for this experiment schematically in Fig. 2.

We considered four contexts or questions, where four geographic regions were presented in pairs within each context. The region pairs within each context had dichotomous values (+ = H) and (− = L), corresponding to possible country investment options and their relative

[14] Damodaran, A. Country Default Spreads and Risk Premiums. Available at: https://pages.stern.nyu.edu/~adamodar/, accessed 28/06/2021.

	Region "Eastern Europe"		Region "Asia"	
	Hungary (H)	Czech Republic (L)	India (H)	China (L)
Please choose two countries for your global portfolio of stocks by picking one country from each of the two regions. Countries are allocated into (H) and (L) categories based on their risk premiums relative to the US stock market.	○	○	○	○

Fig. 3 Example of country investment questions given in c_1

levels of riskiness. The setup of the dichotomous choice combinations followed a R_4 system, given by a 4×4 matrix with 4 contexts (questions) and 4 contents (regions), see Fig. 2.[15]

Before making their investment choices, participants were instructed to select their global stock portfolios by combining one low-risk and one high-risk country fund in the first three contexts, and either two low-risk or two high-risk country funds in the fourth context.[16] This condition was explained to participants from the perspective of global diversification and their clients' risk preferences, as the participants in the experiment acted as fund managers. As such, the participants had always to select between two possible country investment combinations as part of their global portfolio management strategy. In c_4, the high and low-risk investments were more correlated by the design. A degree of diversification was still present due to the selection of country investments from different geographic regions with diverese investment risk profiles.

After each context the subjects were asked about their subjective perception of the riskiness of the four regions relative to the U.S. stock market. This question was devised to account for the possible impact of participants' perception of the riskiness of the geographic regions. Participants were also asked about the motivations behind their specific country investment choices.[17] In Fig. 3 we exemplify the investment questions from c_1.

4.2.2 Experiment 2: adding DJIA shares to a well-diversified portfolio

The stock selection experiment had the same design as Experiment 1 in terms of question structure and rank of the cyclic system. Instead of making investment decisions related to

[15] The display of high and low-risk countries as well as the position of the regions on the display were randomised.

[16] For the background analysis we have collected all possible correlations (i.e., both negative and positive correlations for choices in each context, presented in a random order). For CbD analysis, in c_4 we used the statistics on (++) and (–) investments.

[17] Please refer to Online Appendix 6 for the types of questions asked.

foreign countries' stock indexes, participants were instructed to add shares of two companies from different sectors, part of the Dow Jones Industrial Index, to a well-diversified portfolio of large, established US companies' stocks. Participants were also informed that their portfolio holdings were equivalent to $28,000 and an equal amount had been invested in each stock. Upon adding the two chosen stocks, the total portfolio investment would consequently reach the value of $30,000.

The relative riskiness of the displayed shares was assessed based on their 5-year historical beta, sourced from the SandP Global Market Intelligence platform, from 2017 to 2021. Participants who participated in investment contexts, $c_1 - c_3$, were instructed to select two stocks from different sectors in such a manner that they always chose a pair of (H) and low (L) risk stocks based on their relative betas. The financial motivation for such "preparation" was to avoid picking highly correlated shares and to maintain a sensible level of systemic risk in their portfolio. In c_4, we asked participants to simultaneously select either a pair of low-risk or high-risk investments. Diversification in this setting was achieved by selecting stocks from different sectors. These instructions were part of the "preparation procedure" aimed at maximizing correlations between the stock investment statistics.

Before participating in each investment context, participants were shown a table with all companies, part of the DJIA, their stock ticker, and the sector, to which they belonged.[18]

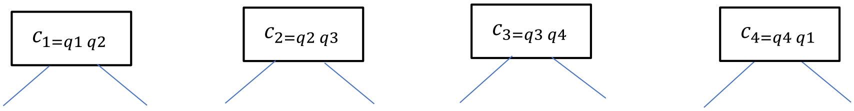
As we only needed to select company stocks from four sectors for our experimental study, we selected the largest sectors that comprise the index at the time of the experiment. The low and high-beta companies were selected from the following sectors: Technology, Consumer staples and Discretionary, Financials, and Industrials. Low beta companies had a beta below one and vice versa for high beta companies.[19] We also collected 5-year daily closing prices for these companies for the period from 2017 to 2021, to get continuously compounded yearly returns. Next, we excluded from the sample three companies that experienced negative average returns over the past 5 years. The remaining 20 companies were double sorted according to their beta and average historical return within each sector. Companies were paired to have approximately the same betas for the low (L) and high (H) risk stock pairs.

The experimental questions were presented in a format consistent with the visualization in the content-context matrix, along with a screenshot of the selection task for c_1, as depicted in Figs. 4, 5.

After making the selection of two stocks from the different sectors to add to their existing portfolio holdings, the participants were asked some follow up questions, (i) their long-term expectations of returns of the stocks in the choice set, shown on a -30%-30% slider, and (ii) their self-reported familiarity with the shown companies on a scale of 1–7 stars, where one star indicated "have never heard of this company" and seven stars indicated "feel very familiar with the company, its brand/s, and products". These follow-up questions were asked to enhance our understanding of the potential determinants influencing participants' choices, particularly as they were required to make investment decisions involving real stocks. Given that participants were exposed to the real names of these stocks, their decisions may have been influenced by various factors identified in the literature. For instance, stock selection may be based on perceived knowledge about the company and anticipated high future returns (Barber & Odean, 2008).

[18] Online Appendix 3 provides a detailed overview of the sampled companies from the DJIA sectors, including their respective 5-year betas.

[19] The healthcare sector was excluded from the choice set due to the heightened attention of newsmakers in the year 2021.



Technology (q_1)	Consumer staples & Discretionary (q_2)	Financials (q_3)	Industrials(q_4)
q_1 Intel (-)	q_2 Home Depot (+)	q_3 Travelers (-)	q_4 Caterpillar (-)
Apple (+)	Walmart (-)	JP Morgan Chase (+)	Boeing (+)

Fig. 4 Content-context matrix experiment 2

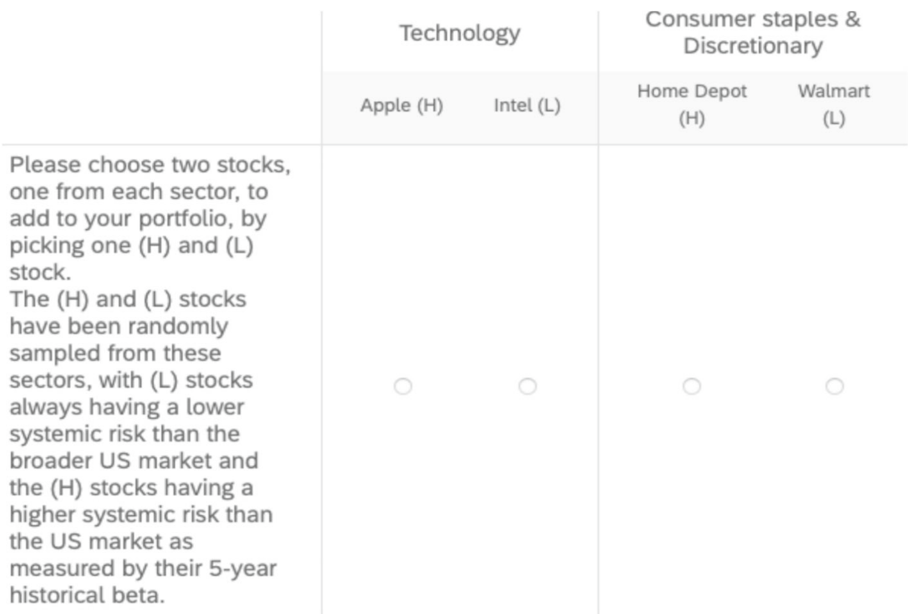


Fig. 5 Example of the selection task for experiment 2 in c_1

Familiarity is also an element, as participants dealt with local U.S. stocks of companies they might know as customers, employees, or through intensive news and social media coverage (Ackert & Church, 2009; Aspara, 2013; Huberman, 2001). Our aim was to observe if these factors made preferences more deterministic across investment contexts.

4.2.3 Additional questions

After participating in both experiments, participants answered a set of demographic and personal questions, such as their investment experience, household wealth, current holdings

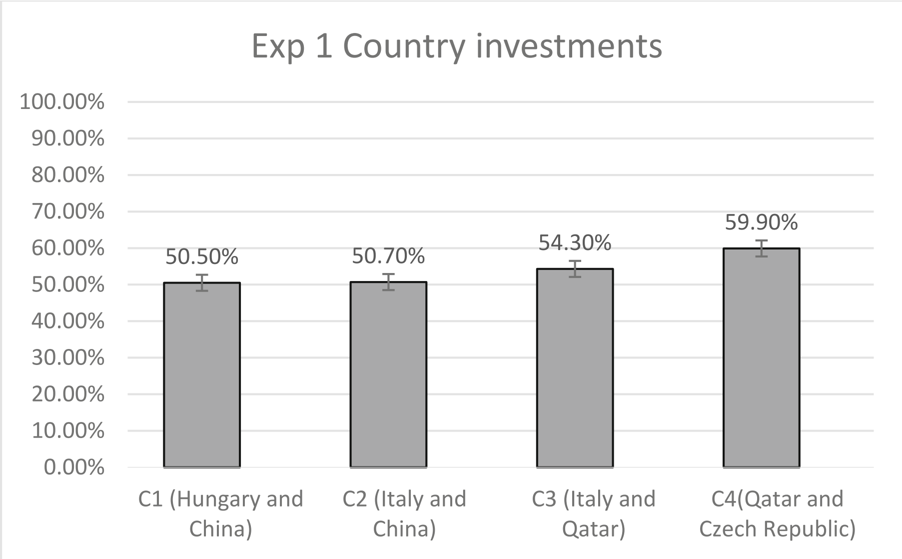


Fig. 6 Experiment 1 choice statistics

of stocks and other financial instruments as well as self-assessed risk-taking in a financial context, etc.

Subsequently, participants were presented with a triad of questions from the cognitive reflection test, a format borrowed from Frederickson (2005), albeit slightly rephrased to circumvent any recognition effect. We asked participants financial literacy questions following Fernandes, et al. (2014). Finally, we also elicited their subjective perception of their investment knowledge and whether they consider themselves an above average investor. We used the results to better understand the characteristics and financial awareness of the sample, as well as to identify potential contextual and universal drivers of investment preferences.[20]

5 Results

Below, we present the results of investment preference statistics across both experiments. From the summary of choice statistics across contexts in Figs. 6, 7, we can see that contextual differences in country investment preferences were more random than in the stock selection settings. In last context, there is a discernible shift in preferences towards low-risk investment pairs.

We conducted a X^2 test for proportions on the between-group statistics to identify any significant changes in investment preferences across choice contexts. A comprehensive summary of the test statistics is provided in Table A4.3 (Online Appendix 4).

We can witness that the significant differences in choice statistics across investment contexts could indicate that preference reversals were driven by contextual factors, i.e., a specific

[20] Please refer to Online Appendix 6 for the formulation of the questions used in our descriptive and inferential statistics.

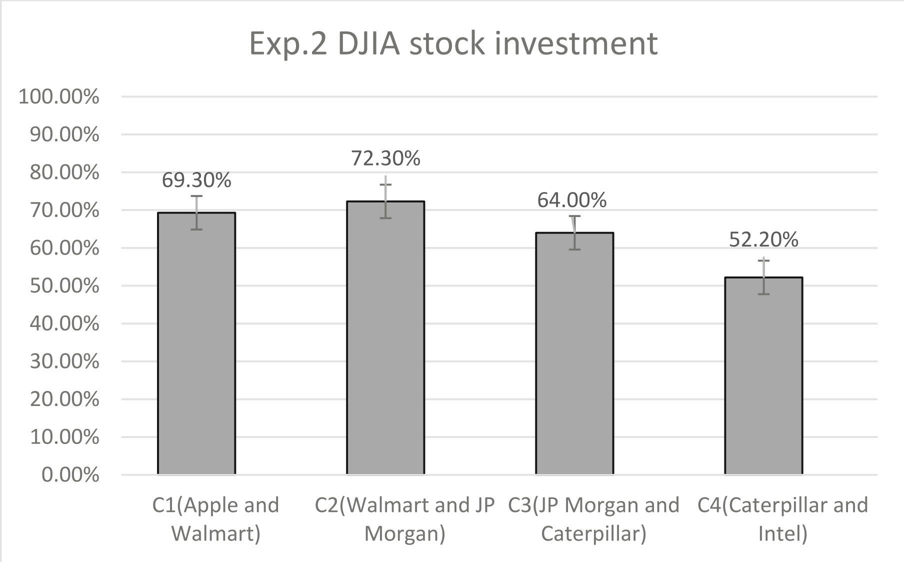


Fig. 7 Experiment 2 choice statistics

country was chosen more often if considered with some other country in the choice set.[21] Marked preference reversals were observed concerning choices between c_4 and c_1. This phenomenon could be attributed to the increased correlations between high- and low-risk pairs, creating a disturbance in participants' preference statistics in the last context.

To explore the existence of 'contextuality proper' beyond the statistical differences in choice preferences across experimental contexts, we will next perform an analysis within the CbD model.

5.1 Statistical analysis within the CbD framework

5.1.1 Contextual probabilities

We performed contextuality tests following the CbD framework introduced earlier.

For the ease of computations, we introduce probabilities to label the response outcomes for each contextual answer, as summarised in Online Appendix 4, Tables A4.1–A4.2. Since we imposed negative correlation constraints on the investment choices (except for last context), the total probability of an answer j was always the same as its marginal probability. This approach allowed us to eliminate the "noise" in our computations of response correlations.

The motivation for imposing selection constraints on participants' investment choices corresponds with the original study of Basieva et al. (2019), which aimed to: "*make the value of the S_{odd} as large as possible, increasing the chances of beating* Δ" (p.1929).

[21] An examination of frequency tables, A4.1- A4.2 (Online Appendix 4) from Experiment 1 reveals that the favourite country preference pairs varied across contexts and the choices were relatively random in the first two contexts. Conversely, results of the second experiment demonstrated a more stable preference distribution, with most participants consistently favoring certain companies, irrespective of the choice context (apart from last context), where low-risk pair was selected by 52.2% of participants.

Table 4 Summary of CbD model computations of contextuality values

Experiments	1. Country investment	2. DJIA stock selection
D = 2-Δ	1.408	- 0.224
D_M	1.42	- 0.228
D_F	1.368	- 0.26

Table 4 summarizes the estimated values of D = 2-Δ in experiment 1 and experiment 2. We also computed D values for male and female participants across all experimental contexts, denoted as D_M and D_F respectively. *A negative value of D in experiment 2 implies lack of true contextuality in decision-making statistics*

We denote in context (c_1) a measurement of random variables R_1 and R_2 as R_1^1 and R_2^1. A value of $+1$ is assigned to H, and -1 to L. By analogy, we label the probabilities of measurements in the contexts, $c_2 - c_4$. As such, the probability of a realizion of the pair of choices is given as:

$$\begin{aligned} p_1 &= P\left(R_1^1 = +1, R_2^1 = -1\right);\ 1 - p_1 = P\left(R_1^1 = -1, R_2^1 = +1\right) \\ p_2 &= P\left(R_2^2 = +1, R_3^2 = -1\right);\ 1 - p_2 = P\left(R_2^2 = -1, R_3^2 = +1\right) \\ p_3 &= P\left(R_3^3 = +1, R_4^3 = -1\right);\ 1 - p_3 = P\left(R_3^3 = -1, R_4^3 = +1\right) \\ p_4 &= P\left(R_4^4 = +1, R_1^4 = +1\right);\ 1 - p_4 = P\left(R_4^4 = -1, R_1^4 = -1\right) \end{aligned} \tag{8}$$

Now, the differences in response distributions (the ‘deltas’) for the same random variable in different contexts can be expressed with the aid of the probabilities defined above. As noted earlier, the term Δ measures the differences between the response distributions for the same question across the four contexts. If $\Delta = 0$, then the cyclic system is consistently connected, and the preference for a certain investment is not influenced by other investment options co-presented within the same context. Put differently, there is no “context-sensitivity” of causal nature in the response data.

$$\Delta = 2|p_1 + p_4 - 1| + 2|p_2 - p_1| + 2|p_3 - p_2| + 2|p_4 - p_3| \tag{9}$$

From Eqs. (6–7) introduced earlier and following Basieva et al. (2019), we introduce a function “D” that is equal to: $(S_{odd} - 2) - \Delta$. From here, CbD equation takes the simplified form:

$$D = 2 - \Delta \tag{10}$$

Consequently, if $D > 0$, then *genuine* (non-classical) contextuality is present in the experimental statistics. This indicates the impossibility of representing such data within a classical probability space.

Our computations of values of D across each experiment are summarised in Table 4. For Experiment 1, the values of D are positive, indicating a presence of contextuality in the country investment choices. For Experiment 2, the value of D is negative, suggesting a lack of contextuality proper across DJIA investment statistics. We further computed D values for the subsamples of male and female participants to test for possible personal characteristics that could influence the emergence of contextuality. We observed that females have a slightly higher Δ value across both experiments.[22] This result may be attributed to some background

[22] We performed a χ^2 test for proportions across all contexts and did not find any significant differences between the choice statistics of males and females.

factors, e.g., higher financial literacy levels observed among men or less distraction from contextual “noise” (Bucher-Koenen et al., 2017).

Following the study of Basieva et al. (2019) and Bruza et al. (2023) we also performed statistical analysis for the observed D values, with the null hypothesis, $D = 0$. We constructed 10,000 independent resamples for each experimental context to obtain 95% confidence intervals. For Experiment 1, the interval was [1.088; 1.492], and for Experiment 2, it was [−0.484; 0.072]. For Experiment 1, the confidence interval for D indicates a significant presence of ‘true’ contextuality beyond the effect of direct influences (i.e., the left endpoint is above zero). In contrast, for Experiment 2, the right endpoints are above zero, indicating a lack of significance with respect to “non-contextuality” (direct influences approximately equal in magnitude to the impact of true contextuality).

Contextuality existence in investment statistics can be interpreted through the lens of “preference construction” and “recorded preferences” as articulated in White et al. (2014). Contextuality is a complex phenomenon and Pothos et al. (2017) document that its manifestation is more pronounced for new, or less recognizable decision-making settings (as has been documented in experiment 1).

For other choices (such as observed in some contexts of experiment 2), individuals may possess more established and firm preferences that are not easily altered. These preferences are independent of other investments considered, meaning they are not influenced by contextual frames, whether internal or external. At the same time, we should interpret the determinism and stochasticity of preferences with caution when viewed through the lens of CbD analysis. The unanimity versus heterogeneity of investment choices across a group of investors, or the determinism versus randomness of choices of a particular investor are influenced by two parameters: the S_{odd} and Δ. These parameters are interconnected in a complex manner and can be affected by direct (causal) influences and hidden contextual factors, which introduce additional stochasticity into the investment statistics.

5.2 Possible drivers of investment preferences

The presence of contextuality can emerge due to hidden variables that influence preferences under frames that appear informationally equivalent. It is challenging to discern the richness of contextual factors, especially in the complex environment of investment choices concerning real financial assets. We aim to explore some possible causal variables discussed in earlier behavioral finance literature. Due to the limited scope, we have confined our analysis to the first two contexts, $c_1 - c_2$.

In experiment 1, we hypothesized that contextuality would be more pronounced in decisions with a greater degree of uncertainty, such as investment choices into foreign markets. As potential contextual investment drivers, we explored the perception of relative investment risk across various regions, familiarity, perceived knowledge about the countries, and future return and risk expectations, given that these countries’ stock indices were perceived as foreign investments by US-based participants. We devised a set of logistic regression model specifications to investigate whether these factors could influence investment preferences in specific choice contexts.

Concurrently, for experiment 2, we hypothesized that for domestic stocks (from the DJIA), participants may have some pre-established and firm preferences, owing to their existing investment experience, information from financial news, or simply “familiarity” with the company names and their products. Our hypothesis aligns with previous studies by Ackert et al. (2005) and Aspara (2013), which found that familiarity with a company's name, recognition of its products and brand, and information on fundamentals can significantly influence stock preferences.

These preferences are expected to be firm and unaffected by context, as stocks subject to familiarity will be perceived as superior investments, independent of other stocks added to the portfolio. Not only can familiarity with the company and its products trigger a firm preference for its shares (Ackert & Church, 2009; Aspara, 2013), but also a belief that the future expected returns of this company will be higher and the risk lower (Huberman, 2001; Kilka & Weber, 2000). Therefore, these preferences would likely be concentrated on "stock picking" as opposed to pursuing, for instance, the benefits of diversification. This emphasis on certain stocks may be attributed to the heightened prior attention towards these companies and their stocks as firstly observed in Barber and Odean (2008).

Based on the preceding discussion, we formulated the following hypotheses for our analysis, which span the contextual statistics of $c_1 - c_2$ in experiments 1 and 2:

H1 *Familiarity with foreign markets and specific stocks enhances the inclination to invest in those assets.*

H2 *Expectations of increasing future returns positively impact the inclination to invest in foreign country stock indexes and individual U.S. stocks.*

5.2.1 Descriptive statistics of the investment drivers

The tables (Tables 5, 6, 7) below provide descriptive statistics for the possible investment drivers that we considered for the two experiments. Table 5 shows that the mean and median risk perceptions for certain regions, particularly the Middle East and Eastern Europe, are relatively higher than for other regions. This observation aligns with historical regional risk premiums. We also solicited country-specific risk and return expectations, along with other variables, to inform possible factors behind the contextual investment choices.

From the frequency distributions presented in Table 6, participants primarily selected country investments based on future return expectations and familiarity. To a lesser extent, their decisions were influenced by future risk expectations and perceived knowledge about the countries and their stock markets.

Table 7 summarizes the descriptive statistics for future return expectations and perceived familiarity levels with each Dow Jones Industrial Average (DJIA) stock, which formed part of the selection set across the subset of contexts we explored.

Table 5 Experiment 1: summary statistics of risk perception for four geographic regions

Region	N	Min	Max	Mean	St. Dev	Median
Risk_Asia	837	0	10	6.17	2.433	6
Risk_Eastern Europe	837	0	10	6.75	2.266	7
Risk_Middle East	837	0	10	7.21	2.204	8
Risk_Western Europe	837	0	10	5.87	2.922	6

Descriptive statistics for the risk perception variable of the four regions (Asia, Eastern Europe, Middle East and Western Europe) on a scale from 0 to 10, where 0 = not riskier than the US stock market and 10 = much riskier than the US market

Table 6 Experiment 1: Frequency table of the four dichotomous variables that were indicated as important by participants in the country investment selection (c1-c2)

	C1	C2
"Higher return expectation in the future"	88.3%	85.2%
"Lower risk expectation in the future"	75.2%	71.9%
"Feeling more informed about countries"	72.3%	70.0%
"I feel more familiar with the countries selected"	78.6%	82.3%
"Selection was completely random"	26.2%	26.1%
N	206	203

The percentages indicate the proportion of participants who answered 'yes' to the above statements. Please also consult Table A5.2 for definitions of these question variables and the original survey questions in Online Appendix 6. Participants predominantly chose investments based on anticipated returns, which were linked to their familiarity with country indexes. Additionally, an element of randomness influenced their selections

We observed high familiarity rankings for the same companies across both contexts that we analysed, with high familiarity often associated with high future return expectations. This pattern was evident for both high and low-beta stocks. It is evident that familiarity differed among stocks in investment set, i.e., some stocks were more familiar to participants.[23]

5.2.2 Binary logistic regression analysis

We examined potential investment determinants across each context utilizing contextual binary logistic regression models.[24] The definitions of the main factors and control variables, employed across both experiments, are specified in Tables A5.1–A5.2 of Online Appendix 5.

Tables 8, 9 present the two model specifications for experiment 1, highlighting factors that could impact investment choices across the two contexts.

For the observed country index selection frequency, the impact of predictor variables was largely unstable and context specific. We could witness that the risk associated with specific regions was a major predictor for choice outcome in c_1.[25] Many of participants' investment choices appeared to be random, as indicated by the significant positive influence of the 'country random' variable in c_2. Control variables, such as cognitive reflection in c_1 (with a positive beta) and investment knowledge in c_2 (with a negative beta) reached significance at 0.05 and 0.01 level, respectively. Cognitive reflection was a positive factor for selecting the most popular country investment pair (c_1), while investment knowledge was a significant factor for selecting the less popular pair (c_2). This potentially indicates the impact of

[23] It is also possible that participants perceived "familiarity" as relative to other stocks within the choice set, i.e., contextual. This is an interesting phenomenon to explore in future studies.

[24] The dependent variable had a dichotomous outcome, corresponding to the more/less popular country pair in each context. Context-specific model specifications were devised for the two contexts (both experiments). As part of the logistic regression analysis, we computed a correlation matrix for the predictor variables for each context analysis. No significant multicollinearity was detected.

[25] The risk perception of the regions was measured on a Likert scale, where a positive relationship indicated higher odds of selecting countries from this region (i.e., a positive relationship between perceived riskiness and investment propensity). The variable '*country_risk_expectation*' was binary, having an inverse interpretation, i.e., "yes" corresponding to lower risk perception. A positive beta value in this context denoted a greater probability of investing in a specific country perceived as low risk.

Table 7 Experiment 2: Summary statistics for familiarity and future return expectations (c1-c2)

Context	DJIA companies in the choice set	N	Return expectations (in %)				Familiarity (score 0–7)				
			Min	Max	Mean	St. Dev	Min	Max	Mean	St. Dev	Median
C1	Apple	212	−30.00	30.00	14.56	8.57	3.00	7.00	5.92	1.12	6.00
	Intel	212	−27.00	30.00	10.65	9.29	1.00	7.00	5.08	1.38	5.00
	Home Depot	212	−16.00	30.00	9.67	9.11	1.00	7.00	5.35	1.36	5.00
	Walmart	212	−21.00	30.00	12.56	7.94	1.00	7.00	5.82	1.22	6.00
C2	JP Morgan Chase	213	−22.00	30.00	12.09	8.73	1.00	7.00	5.26	1.48	6.00
	Travelers	213	−19.00	30.00	8.66	9.86	1.00	7.00	4.16	1.75	4.00
	Home Depot	213	−23.00	30.00	10.06	8.88	2.00	7.00	5.59	1.30	6.00
	Walmart	213	−22.00	30.00	13.54	8.49	3.00	7.00	6.19	0.93	6.00

Participants exhibited higher return expectations for certain stocks, which correlated with their stated familiarity with these stocks

Table 8 Panel A, country selection drivers – Binary logistic regression (C1). The dependent variable is taking value 1 for the more popular country investment pair

Panel A	(I)	(II)	(III)
DV (Hungary (H) ∩ China (L) = 1)			
Risk_Asia	0.141 (4.554)**	0.128 (3.419)*	−0.017 (0.014)
Risk_Eastern_Europe		0.042 (0.349)	−0.115 (0.573)
Interaction term risk Asia ×Eastern Europe			0.025 (1.355)
Country_familiar	−0.009 (0.001)	−0.030 (0.006)	−0.034 (0.008)
Country_return_expectation	0.210 (0.200)	0.176 (0.140)	0.139 (0.770)
Country_risk_expectation	−0.347 (1.028)	−0.327 (0.900)	−0.341 (0.969)
Country_informed	0.199 (0.310)	0.212 (0.348)	0.183 (0.258)
Country_random	0.479 (0.310)	0.463 (1.576)	0.416 (1.238)
Risk_attitude	−0.014 (0.030)	−0.013 (0.029)	−0.013 (0.027)
Investments_knowledge	0.008 (0.009)	0.001 (0.000)	−0.002 (0.000)
Fin. Lit	−0.102 (0.842)	−0.097 (0.756)	−0.100 (0.779)
Trading_experience	−0.264 (0.442)	−0.285 (0.513)	−0.286 (0.514)
CR	0.376 (5.772)**	0.375 (5.746)**	0.371 (5.639)**
Gender (m. = 1)	−0.198 (0.437)	−0.186 (0.385)	−0.214 (0.502)
Age	0.000 (0.001)	0.000 (0.001)	0.001 (0.005)
Constant	−0.895	−1.022	−0.055
Nagelkerke $\mathbf{R}^2$	0.076	0.078	0.086
Observations	206	206	206

The impact of the perception of the overall riskiness of the regions, where the investment countries were located in relation to the U.S. market, familiarity with the countries, expectations about future return and risk profile of the countries, as well as overall risk attitude, CR score and other control variables. Wald test statistics in parentheses,, *p < 0.1, **p < 0.05, ***p < 0.01

Model (I) specification includes risk perception of one region; Model (II) specification includes risk perception of both regions from which the countries' stock indexes were selected; Model (III) introduces an additional interaction term, to test for a possible interaction (amplification) of joint risk attitude between these two regions upon choice outcome. We observe that the risk perception of the "Asia" region is a primary driver of the choice statistics in this context. This effect weakens when the risk perception of the "Eastern Europe" region is also considered. Besides the positive impact of the CR score, no other significant drivers were identified. This could suggest hidden joint effects, such as cultural and social background, which we did not account for

hidden factors, such as job-related experience, previous investments, higher business news coverage or attention to these countries. We recap that the distribution of choices between the investment pairs in the first experiment was largely diverse, suggesting that no group of participants had a strong preference for specific investment countries.

The analysis results in Panels C-D for experiment 2, summarized in Tables 10, 11, indicates that familiarity and future return expectations positively influenced the likelihood of selecting the more popular stock pairs (e.g., Apple and Walmart in c_1). This consistent pattern across both contexts suggests the presence of some universal drivers for investment choices, i.e., a higher degree of determinism.

Table 9 Panel B, country selection drivers – Binary logistic regression (C2). The dependent variable is binary, taking the value of 1 for the more popular investment pair

Panel B	(I)	(II)
DV (Italy (H) ∩ China (L) = 1)		
Risk_Asia	−0.128 (2.817)*	−0.136 (0.091)*
Risk_Western_Europe		0.021 (0.094)
Country_familiar	0.040 (0.008)	0.051 (0.013)
Country_return_expectation	0.679 (1.926)	0.667 (1.841)
Country_risk_expectation	0.712 (4.176)**	0.706 (4.087)**
Country_informed	0.186 (0.264)	0.184 (0.258)
Country_random	−1.045 (7.025)***	−1.065 (7.088)***
Risk attitude	0.061 (0.614)	0.059 (0.581)
Investments_knowledge	−0.276 (8.684)***	−0.278 (8.750)***
Fin. Lit	0.159 (1.487)	0.163 (1.555)
Trading_experience	0.043 (0.010)	0.033 (0.006)
CR	−0.191 (1.363)	−0.176 (1.050)
Gender (m. = 1)	−0.040 (0.014)	−0.27 (0.006)
Age	−0.001 (0.009)	−0.001 (0.006)
Constant	1.116	1.044
Nagelkerke $\mathbf{R}^2$	0.189	0.190
Observations	203	203

The impact of the perception of the overall riskiness of the regions, where the investment countries were located in relation to U.S. market, familiarity with the countries, expectations about future return and risk profile of the countries, as well as overall risk attitude, CR score and other control variables. Wald test statistics in parentheses,, *p < 0.1, **p < 0.05, ***$p < 0.01$

Model (I) specification includes risk perception of one region. Model (II) specification includes risk perception of both regions from which the countries' stock indexes are selected in C2. We omitted here the model consisting of the interaction between the countries' risk attitudes, as no significant impact was detected

6 General discussion

Building upon previous research that uncovered contextuality beyond the boundaries of informational impact, we endeavored to quantify contextuality in pairwise investment choices through the perspective of two experiments, concerning global investments and individual stock selection.

In Experiment 1, we observed contextuality that extended beyond direct influences. However, in Experiment 2, the impact of direct influences was more pronounced, effectively nullifying the maximum contextual correlations that would otherwise exist (i.e., when $\Delta = 0$). We hypothesized, and demonstrated through contextual logistic regression analysis, that participants' stock selections were predominantly influenced by their familiarity with specific stocks and their expectations of these stocks' future returns. The impact of these predictors was largely consistent across the two contexts we considered in our analysis.

The behavior of participants in country index investments exhibited a higher degree of randomness: individual choices were less deterministic and more diverse across the entire sample of participants. This could be yet another element that affected the size of "*D*" function in the CbD model as suggested by Basieva, et al. (2019).

Table 10 Experiment II: Binary logistic regression analysis on DJIA stock selection decision. (The dependent variable is binary, taking the value of 1 for the more popular stock investment pair).Panel C, DJIA stock selection drivers (C1)

Panel C	(1)	(2)	(3)
DV (Apple ∩ Walmart = 1)			
Apple_Return_expectation		0.077 (9.605)***	0.051 (3.669)*
Intel_Return_expectation		−0.058 (5.136)**	−0.046 (3.133)*
Home_Dep._Return_expectation		−0.055 (4.692)**	−0.043 (3.133)*
Walmart_Return_expectation		0.086 (7.562)***	0.084 (6.388) **
Apple_Familiarity	0.585 (10.860)***		0.517 (6.833)***
Intel_Familiarity	−0.446 (7.761)*		−0.397 (5.363)**
Home_Dep_Familiarity	−0.090 (0.342)		−0.008 (0.002)
Walmart_Familiarity	0.332 (4.071)**		0.131 (0.516)
Risk attitude	0.053 (0.391)	0.086 (1.038)	0.074 (0.702)
Investments_knowledge	−0.184 (2.989)*	−0.245 (4.560)**	−0.259 (4.381)**
Fin. Lit	0.081 (0.398)	0.165 (1.564)	0.153 (1.238)
Trading experience	0.635 (1.317)	0.588 (1.096)	0.742 (1.565)
CR	0.295 (2.678)	0.392 (4.783)**	0.365 (3.769)*
Gender (m. = 1)	−0.418 (1.413)	−0.296 (0.704)	−0.372 (1.011)
Age	0.015 (0.994)	0.009 (0.338)	0.014 (0.755)
Constant	−2.084	−0.304	−1.935
Nagelkerke $\boldsymbol{R}^2$	0.235	0.240	0.300
Observations	212	212	212

Model (I) includes the impact of familiarity with the companies in c_1 choice set in upon choice statistics. Model (II) specification tests the impact of future return expectations of the choice companies upon selection outcome. Model (III) includes both factors; future return expectations and familiarity with the companies. Wald test statistics in parentheses, $*p < 0.1$; $**p < 0.05$, $***p < 0.01$. We observe that familiarity with specific companies and expectations of higher future returns are significant predictors of investments in these stocks. Additionally, familiarity with less popular companies indicates a significant propensity to choose these companies, as evidenced by negative betas with respect to the more popular companies

Following the strand of literature on “constructive preferences” we can interpret settings where contextuality is present as choices across questions/investments containing a degree of uncertainty or indeterminism (Kahneman & Snell, 1992; Schwarz, 2007; White et al., 2014; Pothos et al., 2017; and Bruza et al., 2023). Our findings are also qualitatively similar to the accounts of “evaluation” studies, on joint versus separate evaluation of questions, where certain hidden features gain prominence when presented in a joint frame (Hsee, 1996; Hsee et al., 1999; McKenzie et al., 2002). For instance, in investment settings, the attributes of individual stocks and the future return/risk expectations of these investments may be perceived differently when considered in isolation versus in comparison to each other. These contextual trading patterns can have implications for portfolio composition and equilibrium asset prices, potentially leading to phenomena such as bubbles and subsequent corrections (Khrennikova & Patra, 2019).

Our key contribution to the studies on contextual, frame-dependent decision-making is the potential quantification of the degree of these constructive influences and a deeper analysis of their multidimensional nature within the Contextuality by Default (CbD) framework.

Table 11 Panel D, DJIA stock selection drivers (C2)

Panel D	(1)	(2)	(3)
DV (JP Morgan Chase ∩ Walmart = 1)			
JP Morgan_Return_expectation		0.064 (5.733)**	0.026 (0.706)
Travelers_Return_expectation		−0.093 (11.442)***	−0.050 (2.847)*
Home_Dep._Return_expectation		−0.080 (8.002) ***	−0.066 (4.256)**
Walmart_Return_expectation		0.046 (2.761)*	0.073 (5.401) **
JP Morgan_Familiarity	0.676 (18.459)***		0.667 (12.979)***
Travelers_Familiarity	−0.793 (20.951)***		−0.751 (15.651)***
Home_Dep_Familiarity	−0.274 (2.533)		−0.230 (1.579)
Walmart_Familiarity	0.293 (2.010)		0.254 (1.283)
Risk attitude	−0.113 (1.156)		−0.130 (1.412)
Investments_knowledge	0.114 (0.734)	0.087 (0.564)	0.100 (0.509)
Fin. Lit	0.058 (0.212)	0.177 (1.940)	0.160 (1.346)
Trading_experience	0.067 (0.019)	0.083 (0.032)	0.306 (0.345)
CR	0.023 (0.14)	0.214 (1.407)	−0.025 (0.014)
Gender	0.119 (0.107)	0.309 (0.793)	0.196 (0.264)
Age	0.014 (0.807)	0.010 (0.487)	0.013 (0.647)
Constant	−0.085	0.107	−0.456
Nagelkerke $\boldsymbol{R}^2$	0.328	0.232	0.384
Observations	213	213	213

Model (I) only includes perceived familiarity with the stocks, model (II) includes future return expectations of the stocks, and model (III) contains both of these variables. Wald test statistics in parentheses, *$p < 0.1$; **$p < 0.05$, ***$p < 0.01$. In this context, familiarity with certain stocks and higher return expectations are significant drivers of investment decisions. Model (III) shows that familiarity is a significant predictor of investment propensity in the more popular choice set of stocks

This includes a fundamental cognitive state change occurring upon the act of measurement, preference formation, or investment decision.

We can also talk about the *incompatibility* of preferences across contexts, where joint probability (frequency) distribution cannot be considered from the distributions across a range of contexts (Atmaspacher & Romer, 2012). As highlighted by Bruza et al. (2023), the indeterminacy of human cognition leads to incompatible decisions that are characteristic of contextuality. This effect might be attributed to the perceived complexity and ambiguity of the choices in experiment 1, stemming from limited information about the respective countries and causing a more contextual perception of these decision tasks, as corroborated by Venkatraman et al. (2006).

In experiment 2, the perception of uncertainty about the individual stock investments was lower. The (perceived) knowledge or 'liking' of the companies, which is also considered a manifestation of familiarity and home bias (Ackert & Church, 2009; Ackert et al., 2005), was a significant predictor of the choice statistics. In more familiar settings, investment preferences exhibit greater determinism, unless other causal factors are introduced, such as higher betas of the assets or a more familiar stock capturing attention within the investment choice set. The influence of information and stock visibility on stock selection is evident in the second experiment, leading to more stable preferences across contexts.

Investment preferences, like other, more general preferences, examined in earlier studies on the emergence of contextuality, often don not pre-exist in the human cognitive state. Instead, they are constructed during the measurement process (e.g., in investment settings) and are influenced by a complex interplay of internal and external factors. It is of great interest for future studies to perform a more granular analysis of such contexts within financial market decisions, both on an individual basis and with respect to aggregate market dynamics.

We also notice that in the present study we aimed to maintain a form of coherence in participants' initial preference states, via rigid contextual investment instructions, as to achieve the maximal level of contextuality 'proper' in their investment choice statistics. Hence, in our study, "context" served as an instructional device for participants, following previous studies on CbD analysis in decision-making. Indeed, capturing the real social and financial context through precise instructions and "state preparation" is challenging. Economic agents may interpret context differently, leading to more heterogeneous investment preferences.

7 Conclusion

This paper represents the first attempt to quantify contextuality in a real investment setting. Our findings contribute further theoretical and methodological insights, emphasizing the critical role of context in influencing decision-making processes, with implications for aggregate market outcomes.

It is important to further explore and integrate such contextual factors into our economic behavior models within investment contexts. By doing so, we can gain deeper insights into the complex dynamics of financial decision-making and develop more accurate predictive models of contextual investment behavior (e.g., under ambiguity).

Ideally, contextuality should be assessed on a more comprehensive scale, for instance, by considering all combinations of DJIA shares, which would correspond to a system of rank fifteen (assuming a selection from all composites of the index). Another generalization of the CbD framework for random variables with multiple realizations was recently proposed by Kujala and Dzhafarov (2021). Future studies could leverage this modified model to measure contextuality in multiset portfolio constructions. A more detailed analysis of the nature of the direct influences and their dynamics across different asset classes and investment settings would also be of interest to shed more light on the distinction between 'context-sensitive' statistics and genuine (non-classical) contextuality of investment choices.

Our experimental findings are the first to detect the existence of contextuality, quantify its influence, and explore its role in financial decision-making and investments. The experiments were designed to highlight the role of contextuality in financial decision-making and to achieve a substantial violation of contextual inequalities that could surpass the effect of direct influences (as asserted in Basieva et al., 2019). In our study, the investment instructions were formulated to minimize the "noise" in contextual investment statistics as much as possible. Future studies could investigate more diverse investment settings by relaxing the initial "priming" to examine the interaction between agents' heterogeneous investment states and the external financial investment context.

In conclusion, our findings suggest that further research, particularly in varied investment environments, could provide valuable insights into how narrow framing and contextual information influence investment strategies, diversification choices, and financial outcomes.

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Declarations

Conflict of interest None.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethics standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Ethics approval from the University of Leicester was obtained with the number, 24550-pk228-ss/bu:finance. Informed consent was obtained from all participants before taking part in the study.

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