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Effects of price path shapes and decision frames on emotions and investment decisions: Experimental evidence

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ABSTRACT

We extend the literature on emotions and financial decisions by varying the agent (private investor, fund manager, delegation to a fund manager) in an investment experiment. We additionally vary the decision situation (buy or sell) and the shape of displayed price paths (convex, concave, or straight). We measure the investment behavior and the emotional valence evoked by the price paths. Independent of the type of agent, we confirm that price path shapes are related to investment behavior and emotions. In particular, concave shapes are associated with lower investments and valence. Finally, we provide evidence for a mediating role of valence.

KEYWORDS

Framing; emotions; investment decisions; portfolio choice; delegated decisions

Introduction

It is not surprising that the image of a laughing child is associated with positive emotions (Lang, Bradley, and Cuthbert 1997). However, it is remarkable that the visualization of numerical data, such as stock prices, can evoke either positive or negative emotional responses (Kennedy and Hill 2018). Additionally, earlier research demonstrates that these visualizations can even influence investor behavior (Cohn et al. 2015; Grosshans and Zeisberger 2018; Nolte and Schneider 2018; Cordes, Nolte, and Schneider 2023). These studies usually consider decision-makers who make investment decisions for themselves.

However, the role of the decision-maker is particularly important for financial decisions. A large number of financial decisions is delegated (Holzmeister et al. 2023): to family members, fund managers, advisors, or – more recently – to artificial intelligence. The influence of the role of the decision-maker is thus particularly important for understanding financial decisions. Previous literature reports a gap in self-other decisions with respect to several dimensions (Polman and Wu 2020). In many financial decisions, this gap pertains to the chosen level of risk. Another important dimension, which has been scarcely investigated in this context, is the difference in emotional responses for varying roles of the decision-maker. Specifically, deciding for others might reduce the emotional response to the decision.

Earlier literature shows that visualized data, such as stock price charts with a convex shape, are perceived as particularly attractive by investors (Spiller, Reinholtz, and Maglio 2020; Grosshans and Zeisberger 2018; Nolte and Schneider 2018). Although data visualizations are a ubiquitous source of information in stock markets, their impact on asset prices is rarely investigated (Bose et al. 2022; Jiang, Kelly, and Xiu 2023).

Related to price charts, Cordes, Nolte, and Schneider (2023) demonstrate that visualizations with a concave (downswing) shape lead to lower investment and negative valence, whereas convex shapes are associated with the opposite pattern. They employ a direct measure of emotional arousal based on psychophysiological indicators. Furthermore, they provide participants with full information on the data-generating process of the price chart, ensuring that the visualization presents irrelevant information and cannot be associated with any news. Additional tests are conducted to confirm that the

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results are not driven by participants with beliefs in mean-reversion or momentum, but are indeed related to the emotions evoked.

In all of the mentioned experiments, the decision-makers act as investors deciding on their own investments. Consequently, the impact of different roles remains unclear. In real markets, agents with different roles interact and trade in various decision situations. Especially for retail investors, delegation of financial decisions is common (Holzmeister et al. 2023). Therefore, understanding the influence of these different roles is highly relevant. Our experiment extends existing results to different decision frames (buy vs. sell, self vs. other, self vs. delegated), focusing on investment decisions and valence ratings.

There is little evidence explaining why convex or concave data visualizations are generally associated with positive or negative valence. In non-financial contexts, Larkin and Simon (1987) and Butcher (2006), among others, show that data visualization can facilitate a better understanding of the data. However, even if the visualization of financial data is irrelevant for the respective decisions, the relation between price charts and investment behavior still holds (Nolte and Schneider 2018; Cordes, Nolte, and Schneider 2023). Haushofer et al. (2008) provide evidence from brain imaging, indicating that the human brain is more sensitive to processing convex than concave shapes. In an economic context, Spiller, Reinholtz, and Maglio (2020) argue that participants' forecasts based on different shapes of data visualization are consistent with extrapolation of recent trends. Cohn et al. (2015), however, argue that changes in risk preferences observed after presenting participants with visualizations of upward and downward stock market trends could be attributed to emotions, in particular fear. The study uses responses of financial professionals, highlighting that these emotional reactions are not limited to inexperienced investors. They further show that invoking fear directly impacts investment decisions, even when it is explicitly unrelated to the decision. These findings suggests that the emotions evoked by price path shapes are not solely based on trend extrapolation or beliefs in mean-reversion (Cordes, Nolte, and Schneider 2023). This view is supported by Duxbury et al. (2020), who propose that emotions such as hope or fear could be activated when an asset's price deviates from the reference price and support their hypothesis with experimental evidence.

In this article, we remain agnostic about the underlying reasons for the emotional reactions of decision-makers. Instead, we explore the robustness of the results concerning convexity vs. concavity, investment decisions, and valence in different decision contexts. For any future empirical research investigating the role of data visualizations for investments, the robustness of previous experimental findings is highly relevant.

We conducted a pre-registered, incentivized online investment experiment with six treatment conditions to extend previous findings in different context frames. We varied whether the decision-maker decided for themselves, for others, or whether the decision was delegated to a fund manager, where the investor is passively exposed to the decision of buying or selling an asset. Alongside the investment decision, we elicited the valence of convex and concave price path shapes across these context frames.

Our findings confirm that, independent of the decision situation or the role of the decision-maker, convex (concave) price charts are associated with higher (lower) investments and valence. This places our subsequent analyses on comparable ground with previous studies (Nolte and Schneider 2018; Grosshans and Zeisberger 2018; Cordes, Nolte, and Schneider 2023). Compared to the benchmark of price paths with no particularly strong degree of convexity or concavity, we show that concave shapes, rather than convex shapes, drive our results. This is in line with the conjecture that individuals react more strongly to negative cues (concave price paths) than to positive cues (convex price paths).

Consistent with our hypothesis, we also observe that this effect is more pronounced under a sell frame, but only when the decision-makers decide for themselves. For both other roles of the decision-maker, there is no significant difference in the effect of price path shapes between buy and sell decisions. Finally, in an additional analysis, we provide insights into the effect channel between price path shapes and investment behavior by conducting a mediation analysis. We find support for the conjecture that the effect of price path shapes can be mainly explained through the channel of emotional valence.

The remainder of this article is organized as follows. In "Literature review and hypotheses", we briefly review the literature on the effects of price path shapes and behavioral effects of decision contexts. We present our experimental design in "Experimental design and data" and discuss the results in "Results and discussion" before concluding in "Conclusion".

Literature review and hypotheses

For a rational, forward-looking decision-maker, past prices and, consequently, price path shapes should not affect decisions as long as they do not reveal any additional information about the data-generating process of the asset. Yet, a number of studies find that the shape impacts behavior, even when it does not convey any relevant information (Nolte and Schneider 2018; Bose et al. 2022; Cordes, Nolte, and Schneider 2023). The specific channel through which shape affects investment behavior is, however, unclear.

Cordes, Nolte, and Schneider (2023) report that price path shapes affect emotional valence. Specifically, they find that exposure to downswing price paths results in lower valence compared to straight paths, and that the direct effect of path shapes on investment behavior disappears when controlling for valence. These findings indicate that a mediating effect of valence may drive the impact of price path shapes on investment behavior.

From a theoretical perspective, the effect of price path shapes on investor behavior might be explained by the risk-as-feelings hypothesis (Loewenstein et al. 2001). If the shape of the price chart impacts emotional valence, the hypothesis would predict that investment decisions are a direct reaction to the emotional state. Emotional valence is one of the two dimensions in the concept of *core affect* described by Russell (2003), where valence describes emotional reactions on the pleasure-displeasure continuum and arousal refers to the activation-deactivation continuum. The direction and magnitude of the effect of different price path shapes might then be explained by specific emotional reactions. For example, Grosshans and Zeisberger (2018) report higher (lower) levels of investor satisfaction for down-up (up-down) paths when the overall return of the sequence is positive. Cohn et al. (2015) argue that the observed effect of visualized boom and bust scenarios in stock markets on the risk aversion of financial professionals is driven by the emotional reaction of fear. In a study employing multi-period investment decisions, Duxbury et al. (2020) report higher levels of fear and disappointment in experimental conditions with price decreases, and higher levels of hope and elation in conditions with price increases.

Besides further exploring the effect channel between price path shapes and investment behavior, investigating the consistency of the effects across different decision contexts is equally important. If changing the decision frame results in different outcomes, identifying a coherent causal framework might be difficult. The majority of existing experimental studies consider (buying) decisions for oneself; the question of how the framing of the decision context impacts these findings has not been systematically investigated yet. This paper addresses that gap. We follow Nolte and Schneider (2018) and define frames in the context of decisions as informationally equivalent representations of a framed message that potentially result in different mental models (Soman 2004).

As the base case, we consider the decision of an investor choosing how much to invest in a risky asset, as applied by Nolte and Schneider (2018) and Cordes, Nolte, and Schneider (2023). Based on previous literature, we identify the following three dimensions, which we explore in our experiment relative to the base case.

1. **Decision-making for oneself vs. for others:** Decision-making for others has gained considerable attention from researchers over the last decade (Polman and Wu 2020). Early studies found no clear difference in choosing gambles (e.g., risky investments) for oneself or others (Slovic, Weinstein, and Lichtenstein 1967; Cvetkovich 1972; Wilke and Meertens 1973; Teger and Kogan 1975). Since retail investors regularly delegate their financial decisions (Holzmeister et al. 2023), understanding potential systematic differences in choices is highly relevant. While there is no comprehensive theory explaining differences in self-other decision making, the risk-as-feelings hypothesis (Loewenstein et al. 2001) provides an explanation in the setting of the different decision-contexts.[1]

   Affective responses can differ for potential outcomes experienced by others compared to those experienced by oneself. For instance, Zhang et al. (2017) show that people deciding for others are less risk-seeking in a loss frame and less risk-averse in a gain frame. Based on previous literature, we argue that concave charts are similar to a loss frame, and convex charts are similar to a gain frame. Therefore, we would expect the impact of the path shape to be higher when deciding for others than for oneself – the negative (positive) effect of concave (convex) charts is amplified because investors are less (more) willing to take risks, leading to even lower (higher) investments. Conversely, decision-makers could be less sensitive to the valence associated with convex (positive valence) and concave (negative valence) price charts when making choices for others, leading to the exact opposite predictions.
2. **Delegation of the decision:** We also explore the delegation of the investment decision, where it is

made by an outside entity, such as a fund manager. While the decision to delegate is related to financial sophistication and trust (see Holzmeister et al. (2023) and references therein), findings on the delegation of financial decisions suggest that for some people, shifting blame to others in the case of a negative outcome is the major driver behind delegation (Shefrin 2007; Chang, Solomon, and Westerfield 2016). This aspect of delegation could impact our experimental findings. If participants in our experiment experience delegation similarly, we would expect weaker differences in valence reactions between convex and concave price charts. However, there is limited research on delegating financial decisions and how investors feel about delegation (Leyer and Schneider 2019), making this dimension of our research more exploratory.

3. **Buy vs. sell:** One of the most well-known behavioral effects of decision-making under risk is the endowment effect: the empirical finding that willingness-to-accept is generally higher than willingness-to-pay (Kahneman, Knetsch, and Thaler 1991). The endowment effect is often associated with a change in reference prices (Knetsch and Wong 2009). We adapt this reasoning to our setup by considering how a sell frame impacts investment choices and the valence of convex or concave price shapes. Baucells, Weber, and Welfens (2011) and Riley, Summers, and Duxbury (2020) argue that looking at a historical stock price and the shape of the price path impact the reference price. Similarly, Carmon and Ariely (2000) argue that the endowment effect arises because buyers and sellers focus on different aspects of the decision situation. Bordalo, Gennaioli, and Shleifer (2012) model the endowment effect based on salience theory. Psychologically-based explanations suggest that selling activates more regions relevant to negative emotions (Weber et al. 2007). In line with such a link to emotional reactions and previous findings on price path shapes, we expect stronger emotional and behavioral reactions for selling than for buying, i.e., stronger positive valence and higher investments for convex, and stronger negative valence and lower investments for concave price charts. Hence, all effects should be strengthened under the sell frame compared to the buy frame.

Finally, we explore the interaction between the framing and the role of the decision-maker. The endowment effect can exist for all three roles investigated in this paper: decision-making for oneself, for others, and by others. However, the strength of the endowment effect may be amplified or mitigated by these different roles. For example, the sense of ownership could be reduced when deciding for others, reducing differences between selling and buying an asset. Similarly, emotional attachment might be generally lower when the decision has been delegated, which may diminish valence differences between the two frames. Conversely, the framing of the decision could also affect the impact of the different roles on valence and behavior. If endowed with an asset, the additional attachment to the asset may lead to a decision for others as if it were for oneself, or it could amplify the emotional response to a delegated decision. However, there is no clear theory guiding any directed hypotheses, so we expect no differences for these interaction effects.

Experimental design and data

The experiment was implemented using the experimental software *oTree* (Chen, Schonger, and Wickens 2016) and utilized a 2×3 between-subjects design, corresponding to two decision situations (buy or sell) and three roles of decision-makers (decision for oneself, decision for others, delegated decision). Figure 1 displays a flow chart of the experiment.[2] Participants were iteratively assigned to one of the six treatments at the beginning of the experiment. They were provided with a brief explanation of the investment task, adapted to their respective treatment, as well as an explanation of the valence task and the payment mechanism before starting the experiment.

Before further explaining the treatment conditions, we focus on the investment decisions all participants had to make. Each participant saw nine different price paths in random order. For each price path, participants had to decide which fraction of an endowment to invest in the associated risky asset. We used three different categories of price paths with varying shapes in each category, following Cordes, Nolte, and Schneider (2023). Previous studies provided participants with additional information on the risky assets to render the price paths irrelevant for the decisions. We are interested in the influence of different decision roles and the results of previous studies are a benchmark for our findings. Thus, as Grosshans and Zeisberger (2018) and Bose et al. (2022), we provided the price paths as the only information on the risky assets. Participants saw three price paths based on real-world stocks and, as in Nolte and Schneider (2018), three price paths which

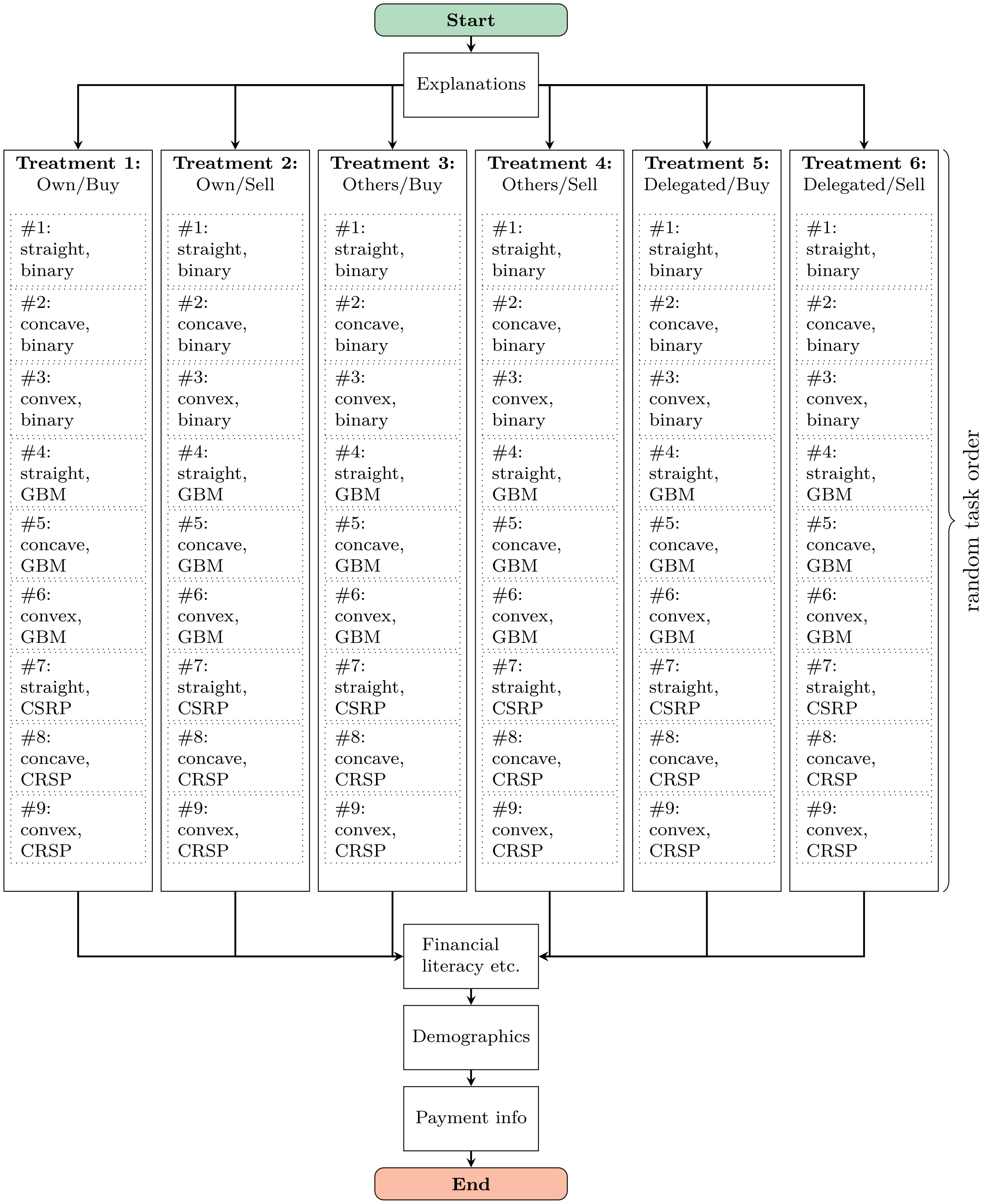
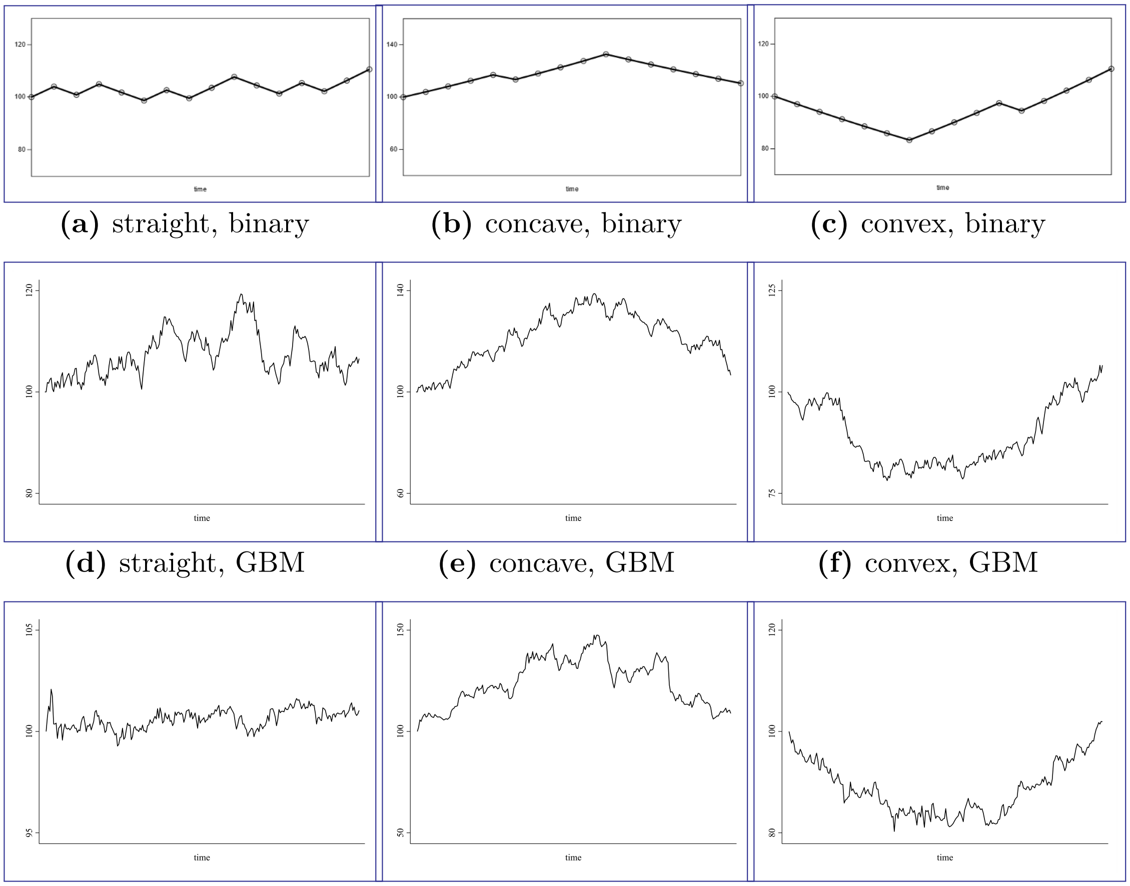


Figure 1. Flow of the experiment. The figure shows the flow of the experiment, including Treatment 1 = Own Decision/Buy, Treatment 2 = Own Decision/Sell, Treatment 3 = Decision for Others/Buy, Treatment 4 = Decision for Others/Sell, Treatment 5 = Delegated Decision/Buy, Treatment 6 = Delegated Decision/Sell. *binary* are charts generated by realizations of a binary lottery, *GMB* are charts generated from a Geometric Brownian Motion (as in Nolte and Schneider (2018)), and *CRSP* are real charts from the universe of assets included in the Center for Research in Security Prices (CRSP) database (https://www.crsp.org).

look realistic but are designed to have identical return distributions for all shapes. Finally, they saw three artificial price paths with the simplest possible underlying return distribution, i.e., multiple realizations of a binary lottery. The last category of price paths was implemented dynamically, i.e., participants observed the development of the risky asset's price live over 15 periods, over a duration of 20 seconds.[3]

In each of the three categories, we included one concave, one convex, and one straight path. Figure 2



(a) straight, binary (b) concave, binary (c) convex, binary

(d) straight, GBM (e) concave, GBM (f) convex, GBM

(g) straight, CRSP (h) concave, CRSP (i) convex, CRSP

Figure 2. Price paths shown to participants by category and shape. The figure shows the nine different price paths shown to participants in all treatments by shape (columns) and type (rows). The first column shows the three straight paths, the second column shows the three concave paths, and the third column shows the three convex paths. Binary charts (first row) are generated by realizations of a binary lottery, GBM charts (second row) are generated from a Geometric Brownian Motion (as in Nolte and Schneider (2018)), and CRSP charts (third row) are charts based on real-world stocks from the universe of assets included in the CRSP database (https://www.crsp.org). The order in which the nine paths were displayed during the experiment was randomized for each participant.

shows screenshots of the nine price paths by category and shape. The different categories provide a high variety of realism and control. There is a tradeoff between these two dimensions. Additional control over the underlying return-generating process reduces external validity, as the associated price paths may look artificial. Conversely, additional external validity comes at the cost of control since the highest degree of realism will have an unknown underlying process. By including all three categories in our experiment – the two extremes and one category in the middle of the spectrum – we can explore our research questions with high external validity and a high degree of control over the return-generating process.

We included a base case and five variations in our experiment, resulting in six between-subjects treatment conditions. The base case was the buy frame with a decision for oneself (Treatment 1), where participants received a fixed endowment of 10,000 monetary units (MU) and had to decide on the fraction to invest in a risky asset, while the remaining part was left in a risk-free asset with zero return. Treatment 2 corresponded to the sell frame with decision-making for oneself, where participants were informed that they had invested in the risky asset one period ago and that their investment was currently worth 10,000 MU. They had to decide on the fraction to keep in the risky asset, while the remaining part was invested in the risk-free asset.

Treatment 3 corresponded to the buy frame with a decision for others, where participants were informed that they were acting as a fund manager who had to allocate a 10,000 MU budget of a client between the risky and the risk-free asset. Treatment 4 corresponded to the sell frame with a decision for others, where participants again took the role of a fund manager investing on behalf of a client under the same conditions as in the sell frame for oneself (i.e., Treatment 2).

In the final two treatments, participants did not make an investment decision but took the role of the client and could only observe the exogenously given decision of a fund manager. In Treatment 5, corresponding to the buy frame, they learned about the fraction of their endowment invested, which was a random integer in the interval [0, 100]. In the sell frame of the delegated decision (Treatment 6), participants learned about the fraction kept in the risky asset by the fund manager, again a random integer in the interval [0, 100].

The flow of the experiment was identical across all treatments. Participants saw the risky asset's historical performance visualized by a price chart. They then decided how much to invest/keep invested in the asset using a slider ranging from 0 to 100%, except for the delegated decisions, where participants only learned how much the fund manager had chosen to invest/keep invested. The slider was implemented without a starting value to avoid anchoring effects (Tversky and Kahneman 1974), i.e., the slider thumb appeared only when participants clicked on the slider bar. After each investment task, we elicited the valence associated with the respective price path. Valence was indicated on a seven-point Likert scale, ranging from *negative* to *positive*, following the measure used in assessing the emotional valence of images by Kurdi, Lozano, and Banaji (2017). To avoid biasing the valence responses, participants received feedback on the realization of their investment decision and their variable payment only at the end of the experiment.

All investment decisions were incentivized. For one of the decisions, the product of the next period's return of the risky asset and the invested amount (plus the non-invested part of the endowment) was converted into real money at a rate of 10,000 MU = 1 GBP, which was paid out to the participants as a variable payment component. The non-invested part of the endowment entered into the payout at its nominal value, i.e., participants were informed that this fraction of the endowment was kept in a risk-free asset with zero interest. For Treatments 3 and 4 (decisions for others), this implicitly assumes a payment structure where the delegatee's payment is linearly dependent on the delegator's (e.g., client's) portfolio return. For Treatments 5 and 6 (delegated decisions), participants also received the product of the next period's return and the exogenously determined invested amount (plus the non-invested part of the endowment). For the real price charts, we applied the actual return of the asset in the following year. For the artificial price charts, we simulated one more period based on the underlying return-generating process.[4] The indicated valence of the price paths was not incentivized.

Finally, after completing the nine investment and valence tasks, participants answered a set of demographic questions and learned about the realization of their variable payment.

The experiment was pre-registered with *AsPredicted*.[5] In total, we recruited 301 participants via *Prolific*, 11 of whom were excluded from the sample based on the pre-registered exclusion criteria.[6] This resulted in a final sample of 290 participants who completed the experiment. Participants were screened to ensure a balanced sample between female and male participants (146 female and 144 male in the final sample), and to only include participants who spoke English fluently. We did not require participants to have any investment experience, as we are mainly interested in the effects of price path shapes on individuals from the universe of (potential) retail investors, who are also most likely to engage in delegated financial decision-making. This sample size is in the range of those of similar experimental studies (e.g., Nolte and Schneider 2018; Grosshans and Zeisberger 2018; Borsboom and Zeisberger 2020; Bose et al. 2022). Summary statistics of the final sample are shown in Table 1.

Results and discussion

We begin the discussion of our results by briefly confirming the general effect of price path shapes on

Table 1. Summary statistics of investment, valence, and participant demographics.

	N	Mean	SD	Min	50%	Max
Investment (%)	1755	45.69	28.79	0.00	48.00	100.00
Valence (7 = positive)	2610	4.38	1.62	1.00	5.00	7.00
Age	290	27.67	8.38	19.00	25.00	73.00
Gender (1 = female)	290	0.50	0.50	0.00	1.00	1.00
Married (1 = yes)	289	0.14	0.35	0.00	0.00	1.00
General risk attitude (7 = highest)	290	4.06	1.48	1.00	4.00	7.00
Financial risk attitude (7 = highest)	290	3.43	1.62	1.00	3.00	7.00
High education (1 = at least Bachelor)	290	0.65	0.48	0.00	1.00	1.00
Income						
Less than 25,000 GBP	290	0.41	0.49	0.00	0.00	1.00
25,000–49,999 GBP	290	0.33	0.47	0.00	0.00	1.00
50,000–99,999 GBP	290	0.14	0.35	0.00	0.00	1.00
100,000–200,000 GBP	290	0.03	0.17	0.00	0.00	1.00
More than 200,000 GBP	290	0.00	0.06	0.00	0.00	1.00
Prefer not to say	290	0.02	0.14	0.00	0.00	1.00
Employment status						
Employed Full-Time	290	0.40	0.49	0.00	0.00	1.00
Employed Part-Time	290	0.10	0.30	0.00	0.00	1.00
Self-employed	290	0.09	0.28	0.00	0.00	1.00
Student	290	0.30	0.46	0.00	0.00	1.00
Seeking opportunities	290	0.08	0.27	0.00	0.00	1.00
Retired	290	0.01	0.10	0.00	0.00	1.00

The table displays summary statistics for the outcome variables and participant characteristics. The number of observations is 195 participants in the active treatments $\times$ 9 decisions = 1755 for investment and 290 participants in all treatments $\times$ 9 decisions = 2610 for valence.

investment behavior and emotions, established in previous research ("Baseline results"). In the main part of our results, we then focus on whether these effects differ in various decision frames ("Main results"). In particular, we investigate whether (1) the effects of price path shapes are stronger when making decisions for oneself compared to deciding for others; (2) the emotional reaction to price path shapes is weaker when observing a delegated decision compared to making a decision for oneself; and (3) effects of price path shapes are stronger in the sell compared to the buy frame. In "Robustness of the main results", we check the robustness of our main findings, applying an alternative econometric approach. Finally, we supply additional results with insights into a potential mediating effect of emotional valence in "Additional results", providing an interesting starting point for future research.

Baseline results

Previous literature shows that convex price charts yield higher invested amounts in investment experiments than concave charts (e.g., Grosshans and Zeisberger 2018; Nolte and Schneider 2018). A potential explanation is that convex charts create positive valence while concave charts create negative valence (Cordes, Nolte, and Schneider 2023). This general finding should be independent of our six treatments. For that reason, we expect that convex (concave) charts should generally yield higher (lower) invested amounts and also a more positive (negative) valence across treatments. Figure 3 shows mean investment and valence by path category, averaged over the treatments, and reports pairwise differences based on t-tests with cluster-robust standard errors.[7] Panel A illustrates that convex (concave) price paths, on average, result in higher (lower) investment compared to the baseline of straight paths. Panel B highlights that reported valence exhibits the same pattern, underlining the potential valence-based explanation. The figure further indicates that the effect of concave charts is stronger compared to that of convex charts for both investment and valence.

Following our pre-registration, we also perform linear regressions to jointly assess the impact of price path shape and between-subjects treatment condition on investment behavior and emotional valence, and confirm the findings presented in Figure 3.[8]

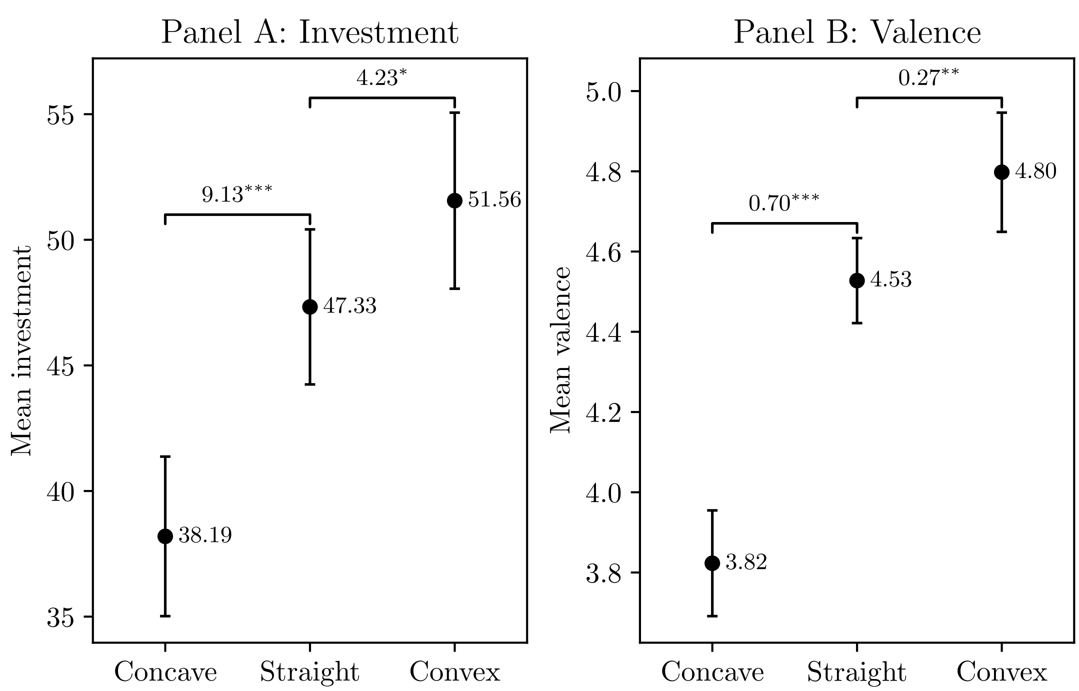


Figure 3. Investment and valence by price path shape. The figure shows investment and valence by price path shape. Panel A (195 participants) shows mean investment in percentage of the endowment and Panel B (290 participants) mean valence in points on a seven-point Likert-scale (1 = negative to 7 = positive) for each of the price path shapes, averaged over treatments. This includes the four treatments in which participants actively decide on the investment for Panel A and all treatments for Panel B. The vertical bars represent 95% confidence intervals around regression coefficients. The differences correspond to regression coefficients for changes in price path shape. Standard errors are clustered at participant-level (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

Main results

Having confirmed this general effect, we now focus on our hypotheses related to the effect strength across treatments.

Table 2 presents the mean invested amount for the four treatments in which participants actively decided on the invested amount, and the differences between buy and sell decisions as well as price paths.[9]

We first look at the buy treatments as a baseline that is comparable to previous experimental studies. In both the own decision and decision for others, the difference in invested amounts between convex and concave price charts is positive in the buy frame (own decision: 36.05 vs. 43.76, not significant; decision for others: 32.93 vs. 45.14, $p < 0.01$). Turning to the valence in the buy frame, Table 3 shows that, in all three treatments, the valence of convex charts is higher than that of concave charts (own decision: 3.94 vs. 4.42, not significant; decision for others: 3.80 vs. 4.73, $p < 0.01$; delegated decision: 3.93 vs. 4.81, $p < 0.001$). Moreover, we see that the drivers of the differences are the concave charts, which also have a significantly lower valence compared to the straight paths in the buy frame (own decision: 3.94 vs. 4.36, $p < 0.05$; decision for others: 3.80 vs. 4.59, $p < 0.001$; delegated decision: 3.93 vs. 4.50, $p < 0.001$), while the convex charts are not significantly differently rated from the straight charts. Overall, we can confirm that, independent of the treatment, convex charts are associated with higher valence while concave charts are related to lower valence, and that this effect is driven by the lower valence of concave charts. This is partly mirrored in the two active decision making treatments, where we observe higher invested amounts for convex charts than for concave charts in the decision for others treatment.

Next, we turn to the endowment effect, i.e., the difference between buy and sell frames across treatments. First, invested amounts are higher in the sell than in the buy frame in the own decision and decision for others treatments for all price path types, and this difference is significant in almost all cases. Second, for the own decision treatments, we confirm that a sell frame leads to stronger differences between price path shapes than a buy frame. Comparing concave and straight, the difference in differences is significant (-2.95 vs. -12.84, $p < 0.01$), indicating that the overall effect is, again, driven by the negative effect of concave paths. In the sell frame, a concave path has a more negative impact on investments than a straight path (39.61 vs. 52.45, $p < 0.001$). This is in line with an emotion-based explanation of the endowment effect and mirrored in the similarly stronger experienced valence of concave price charts (3.58 vs. 4.66, $p < 0.001$), which is also significantly higher compared to the buy frame (difference in differences: 0.66, $p < 0.05$). Being already invested activates stronger emotional responses, especially in the domain of lower valence. These results are intuitive for three reasons. First, negative events have a stronger impact on judgment and decision making in general than positive events (Baumeister et al. 2001). Second, concave paths may remind the investor of downswings or negative economic events, causing fear. Convex paths, in contrast, may be associated with positive economic events and thus are more related to hope. Fear, in particular, is a stronger emotion than hope (Dalley and Buunk 2011). Third, negative emotions trigger a stronger response in the autonomic nervous system (Collet et al. 1997; Etzel et al. 2006; Rainville et al. 2006). This is particularly important as similar effects also

Table 2. Investment analyses.

	Concave	Straight	Convex	Concave − Straight	Convex − Straight	Convex − Concave
Own Decision						
Buy ($N = 51$)	36.05***	39.01***	43.76***	−2.95	4.75	7.71
	(3.00)	(3.31)	(3.16)	(2.61)	(3.80)	(4.02)
Sell ($N = 50$)	39.61***	52.45***	59.97***	−12.84***	7.52	20.36***
	(3.29)	(2.78)	(3.65)	(2.74)	(4.01)	(5.13)
Buy − Sell	−3.55	−13.44**	−16.21***	9.89**	−2.77	−12.65
	(4.44)	(4.31)	(4.81)	(3.77)	(5.50)	(6.48)
Decision for Others						
Buy ($N = 47$)	32.93***	43.94***	45.14***	−11.01***	1.21	12.21**
	(3.23)	(3.14)	(3.49)	(2.60)	(3.53)	(4.11)
Sell ($N = 47$)	44.28***	54.30***	57.49***	−10.02***	3.18	13.21**
	(3.31)	(2.87)	(3.48)	(2.98)	(3.22)	(4.45)
Buy − Sell	−11.35*	−10.37*	−12.35*	−0.99	−1.98	−0.99
	(4.61)	(4.24)	(4.91)	(3.93)	(4.76)	(6.02)

The table reports investments for the three different price path shapes, by treatment, for the active treatments (i.e., Treatments 1 to 4). The first three columns present averages for each price path shape (Concave, Straight, and Convex). The last three columns present differences in average investments between Concave and Straight, Convex and Straight, and Concave and Convex shapes, all by treatment. All values are measured as a percentage (0–100%) of the available endowment. Cluster-robust standard errors of regression coefficients are reported in parentheses (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

Table 3. Valence analyses.

	Concave	Straight	Convex	Concave − Straight	Convex − Straight	Convex − Concave
Own Decision						
Buy ($N = 51$)	3.94***	4.36***	4.42***	−0.42*	0.06	0.48
	(0.16)	(0.16)	(0.18)	(0.20)	(0.26)	(0.28)
Sell ($N = 50$)	3.58***	4.66***	5.07***	−1.08***	0.41	1.49***
	(0.18)	(0.14)	(0.18)	(0.21)	(0.24)	(0.32)
Buy − Sell	0.36	−0.30	−0.65*	0.66*	−0.35	−1.01*
	(0.24)	(0.21)	(0.26)	(0.29)	(0.35)	(0.42)
Decision for Others						
Buy ($N = 47$)	3.80***	4.59***	4.73***	−0.79***	0.14	0.93**
	(0.18)	(0.13)	(0.19)	(0.18)	(0.23)	(0.29)
Sell ($N = 47$)	3.96***	4.62***	5.02***	−0.66***	0.40	1.06***
	(0.19)	(0.12)	(0.18)	(0.16)	(0.23)	(0.31)
Buy − Sell	−0.16	−0.03	−0.29	−0.13	−0.26	−0.13
	(0.26)	(0.18)	(0.26)	(0.24)	(0.32)	(0.42)
Delegated Decision						
Buy ($N = 49$)	3.93***	4.50***	4.81***	−0.57***	0.31	0.88***
	(0.12)	(0.12)	(0.18)	(0.15)	(0.22)	(0.20)
Sell ($N = 46$)	3.73***	4.45***	4.75***	−0.72***	0.30	1.02***
	(0.15)	(0.12)	(0.19)	(0.21)	(0.20)	(0.28)
Buy − Sell	0.19	0.05	0.06	0.15	0.01	−0.14
	(0.19)	(0.17)	(0.26)	(0.26)	(0.29)	(0.34)

The table reports valence for the three different price path shapes, by treatment, for all treatments. The first three columns present averages for each price path shape (Concave, Straight, and Convex). The last three columns present differences in average investments between Concave and Straight, Convex and Straight, and Concave and Convex shapes, all by treatment. All values are measured on a seven-point Likert-scale ranging from negative (1) to positive (7) valence. Cluster-robust standard errors of regression coefficients are reported in parentheses (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

hold for being invested compared to not being invested (Weber et al. 2007).

Second, for the treatments involving decision-making for others, we did not expect a significant difference between the invested amounts in buy and sell decisions for convex and concave price charts. While the effect of convex and concave price charts on invested amounts is present and highly significant (again, driven by the effect of concave price paths), we do not see a significant difference-in-differences. The same picture emerges when it comes to the valence ratings.

Finally, for the delegated decisions, we observe the same pattern. Similarly to deciding for others, there is no amplification of experienced valence between the buy and the sell frame. The endowment effect seems to be mitigated when investors do not decide for themselves. This could be due to lower emotional involvement with the decision and, therefore, a reduced emotional response to being endowed with the asset. However, while we can clearly show that there is some relation between endowment and the role of the investor, we leave further exploration of the underlying (psychological) mechanisms of this effect to future research.

In the final step, we briefly investigate the differences-in-differences for investment and valence across the roles of the decision maker, and the buy and sell frame. The results are reported in Tables 4 and 5. Most differences between decision roles are insignificant, with the exception that deciding for others makes the decision more sensitive to differences in price path shapes. This result is in line with the risk-taking conjecture from the literature.

Table 4. Investment differences-in-differences for price path shapes between decision for others and own decision treatments.

	Concave − Straight	Convex − Straight	Convex − Concave
Buy	−8.05*	−3.55	4.51
	(3.66)	(5.16)	(5.72)
Sell	2.82	−4.34	−7.15
	(4.03)	(5.12)	(6.75)

The table reports differences in the differences between price path shapes between the decision for others and the own decision treatments by decision frame (buy or sell) for the two active treatment groups for investment. Investment is measured as a percentage (0–100%) of the available endowment. Cluster-robust standard errors of regression coefficients are reported in parentheses (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

However, as noted above, there is a gap in research on self-other decisions with respect to several dimensions (Polman and Wu 2020); and how these different dimensions, such as risk-taking and emotional involvement, might interact has hardly been investigated yet. The same holds for the role of delegation and emotional reactions to it. Therefore, we do not want to over-interpret (mostly insignificant) results but leave it for future research to focus on this interplay of dimensions.

Robustness of the main results

To test the robustness of our main findings, we employ an additional, alternative empirical strategy.[10] For both *investment* and *valence*, we conduct a mixed Analysis of Variance (ANOVA), with the between-subjects treatment condition as a between-factor and the price path shape (*concave*, *straight*, *convex*), which

Table 5. Valence differences-in-differences for price path shapes between treatment groups.

		Concave − Straight	Convex − Straight	Convex − Concave
Own vs. Others	Buy	−0.37	0.08	0.45
		(0.27)	(0.35)	(0.40)
	Sell	0.42	−0.00	−0.42
		(0.27)	(0.33)	(0.45)
Own vs. Delegated	Buy	−0.15	0.25	0.41
		(0.25)	(0.34)	(0.35)
	Sell	0.36	−0.10	−0.46
		(0.30)	(0.31)	(0.42)
Others vs. Delegated	Buy	0.22	0.17	−0.04
		(0.24)	(0.31)	(0.35)
	Sell	−0.06	−0.10	−0.04
		(0.26)	(0.30)	(0.42)

The table reports differences in the differences between price path shapes between treatment groups by decision frame (buy or sell) for valence. Valence is measured on a seven-point Likert-scale ranging from negative (1) to positive (7). Cluster-robust standard errors of regression coefficients are reported in parentheses (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

varies over decisions within-participants, as a within-factor.[11] This way, we can simultaneously test for the main effects of treatment and price path shape, as well as all two-way interactions, on investment behavior and valence. However, compared to our main empirical strategy, this approach does not allow to immediately take into account the potential correlation of error terms over participants' responses and the straightforward inclusion of difference-in-difference effects. We then conduct pairwise post-hoc tests. For brevity, the detailed results of these analyses are reported in the Online Appendix.

We can confirm our baseline finding (see Figure 3) that price path shape is significantly related to both *investment* and *valence*. Further, for both outcome variables, we find that the two-way interactions between treatments and price path shapes are not jointly significant. This is in line with our main findings, where we report that the differences in investment and valence between buy and sell decisions for each of the price path shapes are only significant in a few cases. When plotting the interactions, however, we see that concave shapes always result in lower investment and valence than convex or straight paths, independent of the treatment condition, consistent with our main findings. In follow-up pairwise tests, we confirm that when accounting for multiple testing, relevant differences of interest remain statistically significant.[12]

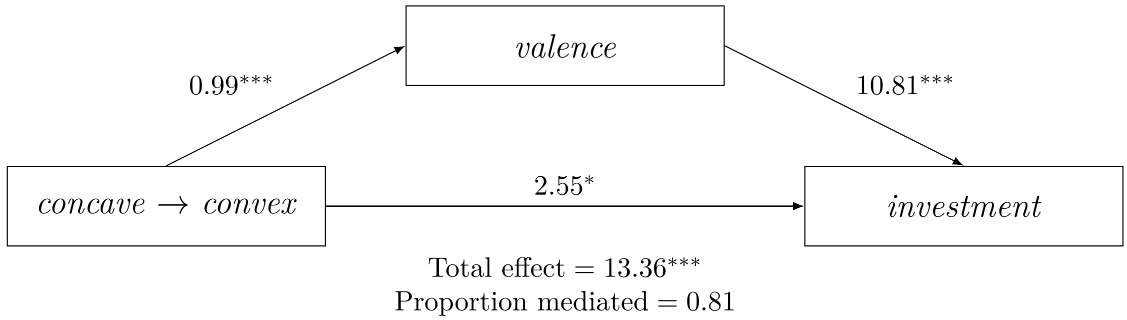
Additional results

In our main analyses, we establish effects of price path shapes on emotional valence and investment behavior. We assume that the effect on investment behavior is mainly driven by the emotional reaction to the price path shapes. However, explicitly investigating this causal chain is not the core focus of our contribution. To gain initial insights into the direction of the effects, we conduct a mediation analysis and investigate the potential mediating role of emotional valence. That is, we test whether the negative (positive) effect of concave (convex) price paths on investment observed in the main analyses can be explained by the effect on valence, which, in turn, affects investment behavior.[13]

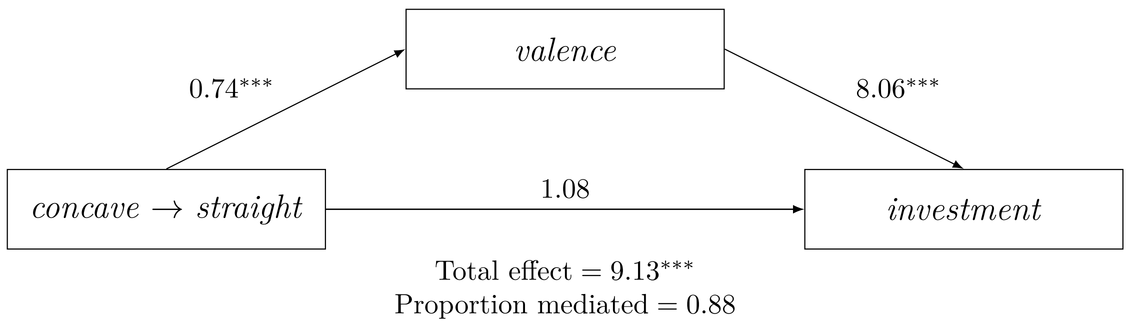
Specifically, we conduct a multilevel mediation analysis, acknowledging the clustered nature of our data (Tingley et al. 2014; Krull and MacKinnon 2001) and control for between-subjects conditions. While price path shape is a within-subjects condition, and valence and investment are also measured at the decision-level, we group observations at the participant level, obtaining participant-level clustered standard errors. Figure 4 displays the main results of these analyses, separately showing the effect of a change in price path shape from *concave* to *convex* and from *concave* to *straight*.[14]

The results indicate that the effect of price path shape is (partly) driven by a mediating effect of emotional valence. Considering a change from a *concave* to a *convex* price path, investment is increased by 10.81 percentage points, similar to the unconditional effect of price path shape, but with a slightly smaller effect size (see "Baseline results"). However, Sub-Figure (a) reveals that this effect is mainly driven by the mediating effect of emotional valence, accounting for 81% of the total effect, while the direct effect of price path shape on investment is small with a weaker statistical significance. Examining a change from a *concave* to a *straight* price path, Sub-Figure (b) shows a similar result. In this case, the proportion of the total effect explained by the mediation is even higher and the direct effect of price path shape is not statistically significant.

Thus, the results from the mediation analysis indicate that the effect of price path shape operates mainly on emotional valence, which, in turn, significantly affects investment behavior. However, the remaining significant direct effect reported for the most substantial change, from *concave* to *convex* price paths, implies that other, additional channels might be at



(a) Effect of change in price path shape from *concave* to *convex*



(b) Effect of change in price path shape from *concave* to *straight*

Figure 4. Multilevel mediation analysis. The figure displays the results of a multilevel mediation analysis with price path shape as the independent variable, *valence* as the mediator variable, treatment condition as a control variable, and *investment* as the dependent variable. Sub-Figure (a) displays the effect of a change in price path shape from *concave* to *convex* and Sub-Figure (b) the effect of a change from *concave* to *straight*. Decision-level observations for the nine distinct decisions per participant are grouped at participant-level. Quasi-Bayesian confidence intervals are simulated with 20,000 runs, respectively. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. More detailed results are provided in the Online Appendix.

work. We emphasize that our mediation analysis only supplies initial insights into the effect channel and further research should focus in more detail on assessing the potential causal relationship between price path shapes and emotional reactions.

Conclusion

The present study investigates the effect of price path shapes on investment and emotional valence, utilizing an incentivized online experiment with three treatment groups: deciding for oneself, deciding for others, and a delegated decision (i.e., a decision by someone else). The results indicate that convex shapes trigger higher investments and a more positive valence than concave shapes. This effect is mainly driven by negative attitudes arising from concave shapes. Furthermore, our study finds that there are generally higher investments and more positive valence for selling than for buying decisions, and that selling decisions amplify differences between price path shapes when investing for oneself. However, this relationship is less straightforward when deciding for others or when the decision is delegated. Finally, we provide initial evidence for the existence of a mediation effect of emotional valence in the relation between price path shapes and investment decisions.

The results indicate that price path shapes evoke emotional responses which then impact decision making. The strength of emotional responses, however, varies depending on the role of the decision maker. Our findings highlight the need for further research on the role of the decision context in shaping investment decisions and emotional valence.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. Besides emotion-based theories to explain shifts in self-others decisions, there are cognitive explanations,

such as different information weighting and information search (Liu et al. 2018; Von Gunten and Scherer 2019). Others focus on the social values hypothesis (Stone and Allgaier 2008). For an excellent literature review, see Polman and Wu (2020).
2. Screenshots and detailed instructions of the experiment can be found in the Online Appendix.
3. For participants, this procedure effectively corresponds to 15 consecutive realizations of a binary lottery. However, to ensure comparable price paths across individuals, the actual sequence of up and down movements was pre-determined for the three shapes of the dynamic paths.
4. On average, the return determining the variable payout was slightly negative because the assets underlying the three real price paths exhibit negative returns in the subsequent period. Therefore, on average, participants in the final sample received 0.99 GBP from the investment decisions in addition to a fixed participation fee of 1.50 GBP.
5. The full pre-registration report, including hypotheses and analyses, can be found at https://aspredicted.org/gngg-nccy.pdf.
6. Eight participants did not pass the attention check, one participant finished the experiment in less than three minutes, and two participants always selected the same answer for either investment or valence.
7. t-tests with robust standard errors clustered at participant-level are implemented as regression coefficients here and in the main results section, employing the package *statsmodels* (Seabold and Perktold 2010) in *Python*. Plot created with the package *matplotlib* (Hunter 2007) in *Python*.
8. Detailed results are presented in the Online Appendix.
9. Here, and in the following steps of the main results, all effects are represented as t-tests with cluster-robust standard errors.
10. We thank an anonymous referee for suggesting this and the mediator analysis of the next section.
11. ANOVA analysis and post-hoc tests are conducted with the packages *afex* (Singmann et al. 2024) and *emmeans* (Lenth 2024) in *R* (R Core Team 2024). Interaction plots are created with the packages *statsmodels* (Seabold and Perktold 2010) and *matplotlib* (Hunter 2007) in *Python*.
12. Given that we conduct pairwise tests for all possible pairs and not only those of interest reported in the main findings, some previously significant differences are not significant under this approach due to the conservative correction for multiple-testing.
13. Mediation analyses are conducted with the package *mediation* (Tingley et al. 2014) in *R* (R Core Team 2024). We thank an anonymous referee for suggesting this additional line of inquiry.
14. More detailed results are provided in the Online Appendix.

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