Salience Bias in Belief Formation

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Abstract

Our study introduces an experimental framework to examine the role of attention in the decision-making process, with a particular focus on its impact on learning and belief formation. In order to identify attention, we draw upon the Salient Theory developed by Bordalo, Gennaioli, and Shleifer (2012). We conduct a two-stage online experiment and uncover several noteworthy findings. Firstly, slightly more than half of the participants show salient thinking characteristics, indicating a proclivity to overweight the standout option among a set of alternatives. Secondly, our results reveal that participants tend to overreact to salient signals and, more importantly, that overreaction is mainly driven by salient thinkers. Additionally, salient thinkers exhibit a greater degree of optimism than others when they receive positive signals, which is further amplified when these signals are infrequent. Lastly, while the salience anomaly is more pronounced in the short term, it disappears over an extended estimation period.

Keywords: limited attention, salient theory, varying signals, overreaction, Bayesian updating

JEL Classification: C90, D83, G41

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1 Introduction

The decision-making process includes various cognitive and psychological aspects. In scientific research, the process is mainly studied as the outcome of evaluating alternatives regarding preferences and beliefs. A significant number of papers in the literature focus on revealed, in other words, observable preferences, by following the assumptions of neoclassical economics. As Caplin (2016) pointed out, the standard economic data provides only what was chosen instead of what was noticed. Here, the raising question waiting to be examined is "What is the effect of the unobservable component like attention?". In this paper, we propose an experimental approach to investigate the role of attention in the decision-making process, specifically, how attention affects the learning process and belief formation.

Contrary to neoclassical theory, it has been shown that we are not able to receive all available information, and furthermore, we fail to process all the received data due to cognitive limitations. As Hirshleifer and Teoh (2003) stated, limited attention is a necessary consequence of the immense amount of information to which we are exposed. Consequently, we allocate our attention across the information set and selectively choose some of the information. In certain cases, this selective attention leads to biased forecasts and incorrect beliefs about the relationship between information (Schwartzstein, 2014). These beliefs shape our understanding of the world and give rise to anomalies in the market. Specifically, in the financial market, holding erroneous beliefs acts as a key driver of financial crises (Gennaioli and Shleifer, 2018).

However, determining what drives attention and measuring (in)attention poses a challenge for researchers. Process tracking methods such as mouselab, eye-tracking (Reutskaja, Nagel, Camerer, and Rangel, 2011), and pupil dilation (Kahneman, 1973) are commonly used to identify and measure attention. On the other hand, a growing body of literature aims to quantify the computational cost of attention in decision-making. Kominers, Mu, and Peysakhovich (2018) demonstrate that even a modest attention cost in computing posterior beliefs can lead to failure to converge on the correct belief. Additionally, Garfagnini (2020) finds that approximately one-fourth of the subjects consistently exhibit a positive attention cost, resulting in less time spent updating their beliefs.

We introduce a novel approach to identifying attention and its consequences in belief formation. We draw upon the Salient Theory developed by Bordalo, Gennaioli, and Shleifer (2012b) (hereafter BGS) to identify attention. Intuitively, the theory suggests that individuals' attention is drawn to the most distinct option in a set of alternatives, leading them to overvalue that salient option. In this study, we apply the theory within a Bayesian framework and address the following question: How does attention affect the learning process and belief formation in the stock market? (Refer to the following section for detailed information about the theory.)

We design a two-stage (attention costless) experiment. Our first objective is to group participants based on their attention mechanism. Individuals who perform compatible with the salience theory are referred to as "local thinkers" (LTs), while the remaining participants are categorized as non-local thinkers (non-LTs). To accomplish this, we present participants with two multiple price lists inspired by Holt and Laury (2002): one featuring a downside salient payoff and the other an upside salient payoff (see Königsheim, Lukas, and Nöth, 2018). Each list consists of 12 decisions, each associated with a corresponding LT parameter. Based on the choices made by the participants, we identify them as LTs if they display risk aversion in the downside salient list and risk-seeking behavior in the upside salient list.

Right after grouping the participants, we analyze their reactions to salient signals. In the second stage, all participants are presented with a choice between a risky outcome (referred to as a "stock") and a sure outcome (referred to as a "bond"). Subsequently, they observe a series of returns from the stock. The stock returns can be drawn from either a good distribution or a bad distribution. In the case of a good-distributed stock, it yields a high payoff with a probability of 70% and a low payoff with a probability of 30%. Conversely, in the case of a bad-distributed stock, it yields a high payoff with a probability of 30% and a low payoff with a probability of 70% (see Kuhnen, 2015).

Different distributions allow us to analyze the effect of the frequency of the signals, which we interpret as representing good times and bad times in the economy. The bond payoff serves a crucial role as a reference point and helps us create upside salient and downside salient returns. Regardless of their choices, participants observe the stock's returns for eight rounds and then provide a probability estimate for having a good stock in each round. Each subject observes the returns for two blocks: one with upside salient returns and one with downside salient returns. In total, they submit 16 probability estimates.

We discovered that slightly more than half of the participants exhibited salient thinking characteristics. Regardless of their classification, all participants displayed an overreaction to salient signals, with the overreaction being predominantly driven by local thinkers (LTs). Additionally, we found that LTs demonstrated a greater degree of optimism compared to non-LTs when receiving positive salient signals. However, the salience effect was found to be short-term in nature, disappearing over an extended estimation period. Lastly, our findings provided supporting evidence for the salience approach in explaining the overall undervaluation of the market. Specifically, participants exhibited pessimism when receiving negative signals in the bad state of the economy, highlighting the presence of pessimism throughout the economy.

Our paper make a contribution to the understanding of belief formation by analyzing three dimensions: (i) differences among groups with different attention mechanisms, (ii) the impact of the salient degree in signals, and (iii) the frequency of the signals.

The rest of the paper is organized as follows: In Section 2, we provide a comprehensive explanation of the Salience Theory along with a review of the relevant literature. The experimental setup is outlined in Section 3. Section 4 presents the primary findings of our study. In Section 5, we discuss the results and draw conclusion.

2 Salient Theory

The Salience Theory (ST), developed by Bordalo, Gennaioli, and Shleifer (2012), provides an alternative perspective to Prospect Theory and aims to demonstrate how attention influences economic decision-making. The theory emphasizes that the characteristics of a specific option that stands out in a given context have a significant impact on the decision process. Salience refers to the attention-attracting option that receives disproportionate weight in decision-making. Individuals who exhibit behavior in line with the theory, referred to as "local thinkers" or "salient thinkers" assign greater weight to the salient payoff compared to other available options.

ST introduces a novelty by providing a psychological basis for individuals' perception of probabilities within the decision-weighting function. Unlike Prospect Theory, ST incorporates a weighting function that considers both probability and payoff. According to Bordalo, Gennaioli, and Shleifer (BGS), the theory's central claim is that individuals assign greater weight to the salient payoff.

Consider a choice problem is described by a set of states S, and each state $s \in S$ occurs with known probabilities π_s. A choice set consists of the lotteries L_i with payoffs x_s^i for each state. Individuals employ a salience function (σ) to evaluate the payoffs and rank them from the most salient to least salient relative to the reference point. The *salience function* $\sigma(x_s^i, x_s^{-i}) : R^2 \rightarrow R$ and that states *salience of* x_s^i *under reference of* x_s^{-i}.

$$\sigma(x_s^i, x_s^{-i}) = \frac{|x_s^i - x_s^{-i}|}{|x_s^i| + |x_s^{-i}| + \theta} \qquad where \qquad \theta \geq 0 \qquad (1)$$

According to the *ordering* property of the σ function, the salience of a state increases with differences between payoff x_s^i and alternative states. If $[x', y']$ is strict subset of $[x, y]$, ordering property requires $\sigma(x', y') < \sigma(x, y)$. Secondly, the salience function needs to satisfy diminishing sensitivity (Weber's law), which implies that salience diminishes by an increase in the absolute value of payoffs. That implies, for any $\epsilon > 0$, $\sigma(x+\epsilon, y+\epsilon) < \sigma(x, y)$. Lastly, the function holds the reflection property, which implies that absolute magnitudes matter more than the sign of payoff in salience.

Consequently, an LT ranks the states in accordance with the salience degree, and then he assigns distorted probabilities for each state as follows:

$$w_s^i = \frac{\delta^{k_s^i}}{\Sigma_r(\delta^{k_r^i} \pi_r)} \qquad \delta \in (0, 1] \qquad (2)$$

$$\pi_s^i = \pi_s w_s^i \qquad (3)$$

In the equation (2), k_s^i represents the rank of the payoff for the state s in S where a lower value of k_s^i indicates higher salience. The parameter δ captures the degree of local thinking, which ranges between 0 and 1. When $\delta = 1$, it corresponds to the rational economic agent as defined in neoclassical economics, indicating a "no salient distortion" case. However, if $\delta < 1$, the agent exhibits salient thinking characteristics and tends to assign higher weight to the most salient state while assigning lower weight to the least salient state. As $\delta \rightarrow 0$, the agent becomes increasingly focused on the salient option. Lastly, a LT evaluates the lottery L_i as follows:

$$V^{LT}(L_i) = \sum_{s \in S} \pi_s^i v(x_s^i) = \sum_{s \in S} \pi_s w_s^i v(x_s^i) \qquad (4)$$

and chooses L_1 over L_2 if and only if:

$$\sum_{s \in S} \delta^k \pi_s [v(x_s^1) - v(x_s^2)] > 0 \qquad (5)$$

ST has wide-ranging applicability across various fields and provides valuable insights into well-known phenomena like the decoy effect, endowment effect, and even judicial decisions (BGS, 2015). When it comes to choice under risk, BGS (2012) applied the theory and demonstrated that individuals exhibiting salient thinking characteristics, referred to as local thinkers (LTs), tend to exhibit risk-averse behavior when facing a salient downside payoff while displaying risk-seeking behavior when encountering an upside salient payoff.

Moreover, the theoretical approach of salience can resolve some puzzling issues in finance. BGS (2013) showed that decision-makers tend to overweight the salient payoffs of assets that deviate the most from the average market payoff, known as the reference point. When facing an upside salient stock, they tend to overprice the assets (growth stocks) and are more likely to experience lower returns. Conversely, when the downside of the stock is salient, they tend to underprice the asset (value asset) and receive higher returns.

Empirical studies conducted by Cosemans and Frehen (2021) in the US stock market provided supportive evidence for the theory. Their findings revealed that investors tend to assign excessive weight to salient past returns when forming their expectations about future returns, leading to lower actual returns. Similarly, Cakici and Zaremba (2022) explored the salience effect using international market data and reported two significant findings. First, they confirmed the existence of the salience effect among microcaps, indicating that investors in this segment also exhibit salience-driven behavior. Second, they found that the salience anomaly tends to have a short-term impact.

Hu, Xiang, and Quan (2023) conducted a study analyzing the influence of salient fund returns on future fund flows. Their findings demonstrated that individuals direct their flows into funds with salient positive returns while withdrawing from funds with salient negative returns. Frydman and Wang (2020) indirectly discovered corroborating evidence for the theory. They highlighted that attributes that receive greater attention also tend to carry more weight in decision-making processes. These empirical studies collectively contribute to the growing body of evidence supporting the role of salience in influencing investor behavior and market outcomes.

Additionally, there is a rapidly growing body of literature consisting of experimental studies aiming to test the salience theory within the context of choice under risk (Dertwinkel-Kalt and Wenner, 2020; Königsheim, Lukas, and Nöth, 2018; Nielsen, Sebald, and Sorensen, 2020). In this particular study, we present a novel experimental design to examine the salience effect on belief formation. To the best of our knowledge, this paper represents the first attempt to investigate the impact of salience on belief updating. The following section provides a comprehensive description of the experimental setting.

3 Experimental Design

We design a two-stage experiment. In the first stage, our aim is to categorize subjects based on the way their attention works. We group them as LTs and others (non-LTs) in this context. Afterward, we display a series of signals on upside and downside salient payoffs to the participants. Following the reception of a signal, they are asked to make a forecast on the probability of having a good stock.

In the identification step, we present participants with two multiple price lists following the approach of Holt and Laury (2002): one with a downside salient payoff and another with an upside salient payoff, as described in Königsheim, Lukas, and Nöth (2018). Each list consists of 12 decisions, and each decision is accompanied by the corresponding LT parameter. As mentioned earlier, participants who exhibit risk aversion in the context of downside salient payoffs and risk-seeking behavior in the context of upside salient payoffs are categorized as LTs. Therefore, based on their choices, we tag participants as LTs if they satisfy both conditions simultaneously.

In both lists, participants make a choice between a risky lottery and a sure payoff. For the price list with downside salient, the sure payoff is 10, and the lottery is $L_1 = (25, p; 0, 1-p)$ where 0 payoff is more salient, in other words, downside salient. (see Table 1)

$$\sigma(0, 10) > \sigma(25, 10)$$

We expect participants to initially prefer the risky lottery over the sure payoff and then switch to the sure payoff at some point. The switching row in the table provides information on both risk attitudes and degrees of local thinking. In the last column on the Table 1, RA stands out for "risk-aversion", and RS stands for "risk-seeking".

Table 1. The multiple price list with downside salient payoff

Row	Range of δ	p	E(L)	Sure Payoff	Diff	Risk
1	0< $\delta < 0.1$	87%	21.75	10	11.75	RA
2	0.1< $\delta < 0.2$	77%	19.25	10	9.25	RA
3	0.2< $\delta < 0.3$	69%	17.25	10	7.25	RA
4	0.3< $\delta < 0.4$	63%	15.75	10	5.75	RA
5	0.4< $\delta < 0.5$	57%	14.25	10	4.25	RA
6	0.5< $\delta < 0.6$	53%	13.25	10	3.25	RA
7	0.6< $\delta < 0.7$	49%	12.25	10	2.25	RA
8	0.7< $\delta < 0.8$	45%	11.25	10	1.25	RA
9	0.8< $\delta < 0.9$	43%	10.75	10	0.75	RA
10	0.9< $\delta < 1.0$	40%	10	10	0	RA
11	1.0< $\delta < 1.1$	38%	9.5	10	-0.5	RS
12	1.1< $\delta < 1.2$	36%	9	10	-0.1	RS

Similarly, for the price list with upside salient payoff, we create the lottery $L_2 = (25, p; 5, 1-p)$ where 25 is (upside) salient payoff, $\sigma(25, 10) > \sigma(5, 10)$. As our objective is to identify LTs, we anticipate that participants exhibit switching behavior within the first ten rows of both lists. Lastly, we display the tables consecutively; however, to avoid any potential order effects, the tables are presented in a random order. [1]

[1]see Appendix B for the screenshots of the experiment.

Table 2. The multiple price list with upside salient payoff

Row	Range of δ	p	E(L)	Sure Payoff	Diff	Risk
1	$0< \delta < 0.1$	3%	5.6	10	-4.4	RS
2	$0.1< \delta < 0.2$	6%	6.2	10	-3.8	RS
3	$0.2< \delta < 0.3$	9%	6.8	10	-3.2	RS
4	$0.3< \delta < 0.4$	12%	7.4	10	-2.6	RS
5	$0.4< \delta < 0.5$	14%	7.8	10	-2.2	RS
6	$0.5< \delta < 0.6$	17%	8.4	10	-1.6	RS
7	$0.6< \delta < 0.7$	19%	8.8	10	-1.2	RS
8	$0.7< \delta < 0.8$	21%	9.2	10	-0.8	RS
9	$0.8< \delta < 0.9$	23%	9.6	10	-0.4	RS
10	$0.9< \delta < 1.0$	25%	10	10	0	RS
11	$1.0< \delta < 1.1$	27%	9.5	10.4	0.4	RA
12	$1.1< \delta < 1.2$	29%	9	10.8	0.8	RA

The second part of the experiment consists of the main body where we analyze the belief updating process across the groups. In this part, all participants are presented with a choice between a risky outcome (referred to as the "stock") and a sure outcome (referred to as the "bond"). The stock can be generated from either a good or bad distribution. If it is a good-distributed stock, it yields a high payoff with a probability of 70% and a low payoff with a probability of 30%. Conversely, if it is a bad-distributed stock, it yields a high payoff with a probability of 30% and a low payoff with a probability of 70%. (For further details, refer to Kuhnen, 2015.) It is important to note that this task does not involve an actual active choice; instead, we utilize the bond payoff as a reference point, which helps us create downside and upside salient returns.

Subsequently, regardless of the choices made, participants observe the stock returns for eight rounds. They then enter a probability estimate of having a good stock in each round. Each subject attends to two blocks, one with upside salient returns and one with downside salient returns. In total, they observe the signals for 16 rounds and submit their estimates 16 times. Combining the different blocks with distribution types results in four different trial conditions, as follows:

(i) upside salient / good - downside salient / bad

(ii) upside salient / good - downside salient / good

(iii) upside salient / bad - downside salient / bad

(iv) upside salient / bad - downside salient / good

Each participant is randomly assigned one of these four trials. In both blocks, we set the same sure payoff (bond payoff) equal to 10. In the upside salient block, the subjects make choices between $(26, p; 8, 1-p)$ and bond payoff where $\sigma(26, 10) > \sigma(8, 10)$. In the downside salient block, we set $(12, p; 4, 1-p)$ as asset return where $\sigma(4, 10) > \sigma(12, 10)$. Once again, to mitigate the potential impact of order effects, the order of the blocks is assigned randomly.

The experiment payment includes three components for the participants. Firstly, they receive a show-up fee as a base payment. Secondly, they are rewarded with the corresponding payoff from a randomly selected MPL (Multiple Price List) row. Lastly, participants have the opportunity to earn a bonus for each accurate probability estimate they provide regarding the likelihood of having a good stock. The summary of the experiment is depicted in the following diagram:

Two MPLs:		**Belief Updating**
One with downside salient (12 choices)		Block 1: Downside salient signal (8 rounds)
$\sigma(0, 10) > \sigma(25, 10)$	$\longrightarrow$	$(12, p; 4, 1-p) \rightarrow \sigma(4, 10) > \sigma(12, 10)$
One with upside salient(12 choices)		Block 2: Upside salient signal (8 rounds)
$\sigma(25, 10) > \sigma(5, 10)$		$(26, p; 8, 1-p) \rightarrow \sigma(26, 10) > \sigma(8, 10)$

4 Results

We designed the experiment via oTree (Chen, Schonger, and Wickens, 2016) and conducted it on Prolific, a well-known platform for experimental studies. We specifically filtered university students as participants to obtain a similar profile as in lab experiments. We had initially 118 participants, but we had to exclude 4 of them due to inconsistent choices in the first stage. The following table provides the summary statistics of the remaining 114 subjects.

Table 3. Summary Statistics

Variable	Mean	Median	SD
Response Time	738.66	654.15	336.09
Age	25.25	21	8.81
Female	0.61	1	0.49
Undergraduate	2.15	2	0.97

From the choices made in the first stage, we found that 59 subjects (51.8%) out of the 114 subjects in our sample exhibited behavior in line with the salience theory. This means that while they demonstrated risk-averse behavior in the MPL with a downside salient payoff, they simultaneously exhibited risk-taking characteristics in the MPL with an upside salient payoff. This finding is relatively higher than the current findings in the literature (Königsheim et al., 2018), where 30%-45% of subjects behaved according to the theory. This discrepancy is likely due to the employment of relatively more salient (higher σ) payoffs in our MPLs.

We observed a relatively higher number of LTs (11 subjects more) when the upside MPL was displayed first. Furthermore, 87% (99 subjects) of the participants exhibited risk aversion in the downside MPL. This ratio decreased in the subsequent list, where 56% (64 subjects) of the participants demonstrated risk-seeking behavior in the upside MPL.

The average switching points for LTs are found to be around the 6th row in the downside MPL and the 9th row in the upside MPL. In terms of the local thinking parameter, we observe that δ differs between the two lists. Specifically, δ is significantly lower in the downside MPL (see Table 4). While the average δ is below 0.7 in the downside MPL, it is above 0.7 in the upside list. However, the overall average of δ is around 0.7, which aligns with the LT parameter proposed by BGS. Therefore, our findings are consistent with the existing literature.

Table 4. Linear Regression on Local Thinking Parameter (δ)

Dependent Variable	LT parameter (δ)
Downside MPL	-0.34***
	(-10.73)
Constant	0.85***
	(37.67)
Observation	114

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

From now onward, we present the results of the second part, which constitute our main findings. Firstly, we analyze how the two types (LTs and non-LTs) update their beliefs when they receive the salient signals separately. To examine this, we utilize linear regression models on the elicited beliefs data.

$$SubjectivePosterior_i = \beta_1 + \beta_2 DownsideSignal_i + \beta_3 ObjectivePosterior_i + \epsilon_i$$

where *DownsideSignal* is dummy variable which takes a value of 1 if the downside signal is salient, and *ObjectivePosterior* indicates the objective Bayesian probabilities. Our findings reveal that participants, regardless of their types, tend to overreact to salient signals (refer to the first column of Table 5 for pooled data). The second and third columns of the table provide results for the subgroups. These results demonstrate that LTs exhibit a strong and significant overreaction to salient signals. However, we did not detect such overreaction among non-LTs. Therefore, it can be concluded that the overall overreaction to salient signals is mainly driven by LTs.

Table 5. Linear Regression of Subjective Posterior

Dependent Variable	Subjective Posterior		
	ALL	LT	NON-LT
Downside Signal	-2.01**	-4.68***	0.85
	(-2.18)	(-3.81)	(0.62)
Objective Posterior	0.48***	0.48***	0.48***
	(31.09)	(23.84)	(20.40)
Constant	26.10***	28.18***	23.77***
	(26.31)	(21.60)	(15.80)
Observations	1,824	944	880
R-squared	0.3509	0.3851	0.3231

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

On the other hand, when analyzing the participants' reactions to rare signals, which include downside salient signals from the good distribution and upside salient signals from the bad distribution, we could not find any significant results.

Then, we specifically focus on different signal types. Table 6 shows the result for signal types and their combinations. Here, the "Upside" column represents all upside blocks, and the “Upside/Good” column represents the block where the upside salient is drawn from a good distribution that refers to observing the upside salient frequently. Other columns follow the same logic.

Our findings indicate that LTs tend to be more overoptimistic than non-LTs when they receive upside salient signals, in other words, good signals. Elicited beliefs of LTs are, on average, 4.8% higher than non-LTs when they receive good signals; the finding is statistically significant. The figure becomes even more pronounced when the good signal is observed infrequently.

In contrast, we do not observe any significant differences between the two groups in the downside salient blocks. In the first stage, we already revealed that the majority of participants exhibit similar risk behavior in such blocks, regardless of their type. Therefore, the absence of differences between the subgroups in the downside salient blocks is expected.

Table 6. Linear Regression of Subjective Posterior in four combinations (all rounds)

Dependent Variable			Subjective	Posterior		
	Upside	Upside/Good	Upside/Bad	Downside	Downside/Good	Downside/Bad
LT	4.75***	3.77*	5.88***	-0.85	0.84	-2.16
	(3.54)	(1.88)	(3.28)	(-0.68)	(0.48)	(-1.19)
Objective Posterior	0.46***	0.49***	0.48***	0.51***	0.43***	0.55***
	(20.55)	(7.98)	(9.92)	(23.83)	(10.06)	(11.77)
Constant	24.77***	22.28***	24.02***	23.33***	27.90***	22.63***
	(16.98)	(4.62)	(14.12)	(18.17)	(9.29)	(13.29)
Observations	912	464	448	912	464	448
R-squared	0.322	0.1231	0.1999	0.3847	0.183	0.2454

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

As our objective is not to test the participants’ memory, we created a costless environment where all previous payoffs were displayed in each round. This allowed participants to observe all previous returns, including the last round. Consequently, we can analyze the evaluation of the forecasting performance of LTs as the rounds progress. Table 7 presents a comparison of the average forecasting performance across all eight rounds with the last round. The results indicate that as LTs make more observations of the salient return, their forecasts tend to converge with those of non-LTs. Consequently, the difference in forecasting between the two groups diminishes by the last round.

Table 7. Linear Regression of Subjective Posterior

Dependent Variable		Subjective Posterior		
	Upside Salient (All rounds)	Upside Salient (Last round)	Downside Salient (All rounds)	Downside Salient (Last round)
LT	4.75***	5.56	-0.85	-3.62
	(3.54)	(1.39)	(-0.68)	(-0.88)
Objective Posterior	0.46***	0.52***	0.51***	0.47***
	(20.55)	(8.89)	(23.83)	(9.00)
Constant	24.77***	23.71***	23.33***	23.13***
	(16.98)	(5.91)	(18.17)	(7.08)
Observations	912	114	912	114

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Therefore, based on our analysis, we can conclude that the salience anomaly exhibits a short-term effect, which aligns with previous literature. Cakici and Zaremba (2022) provide empirical evidence supporting the notion that the salience effect is strong in the short estimation period but weakens over time, eventually disappearing in the long estimation period.

4.1 Testing time-varying salience

In this section, our focus is to investigate the time-varying salience effect. Bordalo et al. (2013) present a theoretical framework in which they argue that investors perceive the downside of risky assets as more salient in unfavorable economic conditions. Consequently, they tend to underprice assets with downside salience, resulting in a positive risk premium.[2]. Following the same logic, when the fundamentals are good and the economy is in a favorable condition, investors shift their focus to the upside prospect of assets. However, due to the limited right-skewness of risky asset payoff distributions, this emphasis on upside salience leads to an overall undervaluation of the market and a positive risk premium.

[2]The price of the asset defines as a function of delivering payoffs' probabilities: $p = x + \pi w G$ where π is the objective probability and w stands for the weighting function.

Our design does not involve any asset pricing steps. However, the findings presented in Table 8 provide supportive evidence for BGS. We interpret "good-distributed blocks" as representing a good state of the economy, and "bad-distributed blocks" as representing a bad state of the economy. When participants receive a downside salient signal (bad news/signal) during difficult times, they tend to underestimate the probability of having a good stock, resulting in the undervaluation of the market. Conversely, we do not observe a similar tendency for an upside signal during favorable times. Instead, our findings show that LTs display over-optimism when the economy is in a good state.

As shown in the first three columns of Table 8, combining all periods, the subjects still tend to be pessimistic, which may lead to a positive risk premium, as BGS claim. However, we argue that the underlying reason for this phenomenon is not solely due to a lack of sufficiently right-skewed stocks. Instead, we propose that it is influenced by the varying local thinking degrees (δ) exhibited by agents across upside and salient cases. We set almost the same salience degree in both cases. While we maintained a nearly identical salience degree in both cases, our findings revealed that in the initial phase of the experiment, δ was lower (higher) for the downside (upside) salient environment. As δ approaches zero, the distortion caused by salience amplifies, leading to a higher level of distortion in the downside salient environment. Consequently, we conclude that this asymmetry across states arises from the differing local thinking degrees.

5 Conclusion

The role of attention in the decision-making process includes many unanswered questions. There are many rooms to be examined and enlightened. By benefiting from the salience theory, we present a novel path to examine how attention affects the belief-updating process. Our paper contributes to the understanding of belief formation by analyzing three key dimensions: (i) variations among groups with different attention mechanisms, (ii) the influence of salient degrees in signals, and (iii) the frequency of these signals.

Our findings reveal that 52% of the subjects align their behavior with the theoretical predictions. During the main stage, we observe that participants do not overreact to rare signals but exhibit a greater reaction to salient signals. Notably, we demonstrate that this overreaction to salient signals primarily stems from subjects displaying characteristics of

Table 8. Time-varying salience

Estimation of subjective posterior in different time periods. *Good times* indicate the stock is drawn from the good distribution. *Downside Salient* and *LT* are dummy variables. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	Subjective Posterior								
	All Times (1)	All Times (2)	All Times (3)	Bad Times (1)	Bad Times (2)	Bad Times (3)	Good Times (1)	Good Times (2)	Good Times (3)
Downside Signal	-3.91***	-2.01**	-2.01**	-4.31***	-3.83***	-3.77***	-3.51**	-0.42	-0.49
	(-3.44)	(-2.18)	(-2.18)	(-3.00)	(-3.00)	(-2.94)	(-2.47)	(-0.31)	(-0.37)
Objective Posterior		0.48***	0.48***		0.52***	0.52***		0.48***	0.45***
		(31.09)	(31.09)		(15.50)	(15.55)		(12.55)	(12.56)
LT			2.01			1.78			2.19*
			(2.18)			(1.39)			(1.66)
Constant	49.40***	26.10***	25.08***	38.34***	26.07***	25.10***	60.08***	27.37***	26.26***
	(61.44)	(26.31)	(22.91)	(37.67)	(21.69)	(18.08)	(59.65)	(9.89)	(9.23)
Observations	1,824	1,824	1,824	896	896	896	928	928	928

local thinking. Moreover, these individuals also display higher levels of optimism compared to non-local thinkers when receiving upside salient signals, particularly in cases where the signals are infrequent. The elicited beliefs of local thinkers, on average, are 4.8% higher than those of non-local thinkers when presented with positive signals, and this difference is statistically significant. However, in the downside salient treatment, being a local thinker has a negative impact on probability estimation, though it is statistically insignificant. This lack of significance may be attributed to local thinkers exhibiting risk aversion when facing downside salient signals, while non-local thinkers likely display a tendency for risk aversion as well. Furthermore, we demonstrate that the salience phenomenon has a short-term effect that diminishes over long estimation periods.

Lastly, we provide supportive evidence for the time-varying salience effect proposed by BGS (2013). We observe that when the subjects are in a bad state, they tend to overreact to downside salient signals, resulting in an overall undervaluation of the market and a positive risk premium. However, we attribute this phenomenon primarily to the varying degrees of local thinking among the participants.

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7 Appendix

A. Participant Instructions

Instruction for the FIRST step of the experiment:

Please read the instruction carefully.

In the following, you will be faced with two lists where each list consists of 12 decisions. Each decision is a paired choice between "Option A" and "Option B". While the payoffs of the two options are fixed for all decisions within the list, the probabilities for "Option A" will vary.

Payment:

After making all of your choices for both lists, one of the 24 decisions will be randomly chosen for your payment. For the option (A or B) you chose in this decision, it will be determined according to the corresponding probabilities. Your payoff is shown in points.(1 point = £0.01)

To summarize:

1- You will be faced with two lists.
2- You will make 12 decisions in each list.
3- For each decision, you will have to choose between "Option A" and "Option B".
4- When you finish, one of the 24 decisions will be randomly picked for your payment.

Please click the "Next" button when you feel ready.

Instruction for the SECOND step of the experiment:

Please read the instruction carefully.

In the following, you will choose between a stock (risky payoff) and a bond (sure payoff). Bond payoff is £10 for sure. Stock payoffs are £12 or £4. The stock can either be good or bad stock.

If the stock is a GOOD one, its payoff is £12 with 70% probability and £4 with 30% probability.

If the stock is a BAD one, its payoff is £12 with 30% probability and £4 with 70% probability.

Task:
Having good and bad stocks are assigned randomly. So, in the beginning, the probability of having a good or bad stock is 50%.

Then you will be asked to choose between the stock and the bond. Regardless of your choice, you will observe the stock's payoffs for eight rounds, and each round, you will be asked for your prediction of whether the stock is GOOD one.

The stock type will remain the same for these rounds.

Payment:
Your payment will be determined by your correct prediction. If your prediction is within 5% of the correct value, you will get 2 points for each correct prediction.

For example: Let's say, in one of the rounds, the correct probability is 80%, and if you enter a number between 76% and 84%, we will add 2 points to your payment. (1 points = £0.01)

To summarize:
1- You will be faced with one stock and one bond. The stock can either be good or bad.
2- Then, you will observe the stock's payoff eight times, and each round, you will be asked to provide a probability estimate of whether the stock is GOOD one.
3- You will gain 2 points for every correct estimate.

Please click the "Next" button when you feel ready.

B. Screenshots of the Experiment

The following two figures present the multiple price list as seen by the participants; in other words, screenshots of the first step of the experiment:

YOUR DECISION

Option A	Option B
25 points with a probability of 87 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 77 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 69 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 63 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 57 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 53 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 49 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 45 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 43 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 40 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 38 %, 0 points otherwise	10 points with a probability of 100 %
25 points with a probability of 36 %, 0 points otherwise	10 points with a probability of 100 %

Figure 1: MPL with downside salient payoff

YOUR DECISION

Option A	Option B
25 points with a probability of 3 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 6 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 9 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 12 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 14 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 17 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 19 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 21 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 23 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 25 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 27 %, 5 points otherwise	10 points with a probability of 100 %
25 points with a probability of 29 %, 5 points otherwise	10 points with a probability of 100 %

Figure 2: MPL with upside salient payoff

The following three figures present the pages of the second part of the experiment:

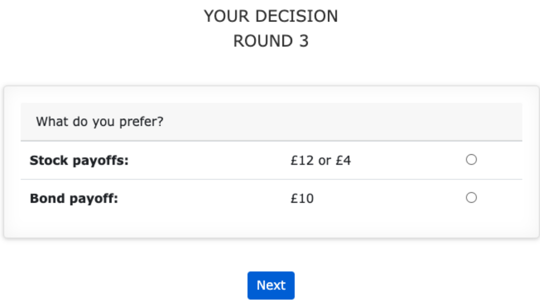

Figure 3: Decision page

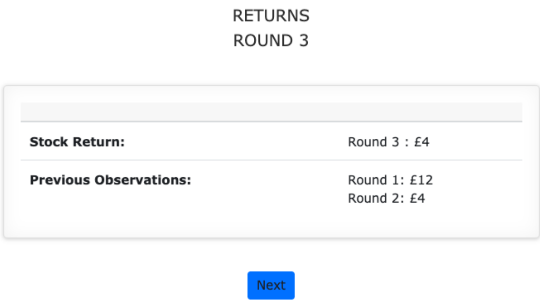

Figure 4: Return observations

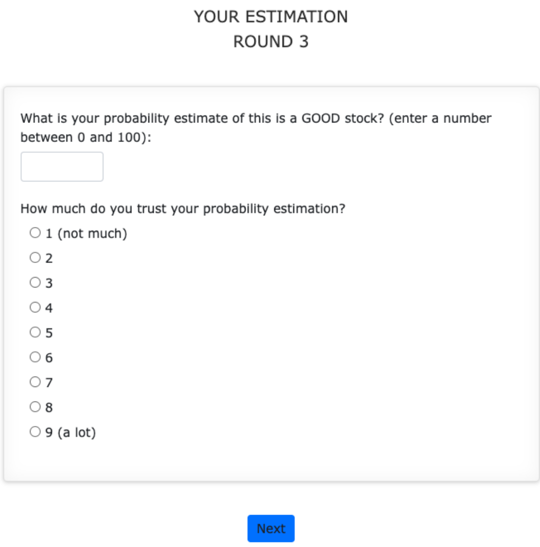

Figure 5: Probability entering

C. Objective Bayesian Posterior Beliefs

The following table shows all possible values for the correct Bayesian posterior where the prior is 50%-50%. The posterior that the stock is the good one, after observing t high outcomes in n trials so far, is given by:

$$\frac{1}{1+\frac{1-p}{p}*(\frac{q}{1-q})^{n-2t}}$$

where p is the prior and q is the probability that a good stock has a high return in each trial; here, it is 70%.

n	t	Probability
1	0	30.00%
1	1	70.00%
2	0	15.52%
2	1	50.00%
2	2	84.48%
3	0	7.30%
3	1	30.00%
3	2	70.00%
3	3	92.70%
4	0	3.26%
4	1	30.00%
4	2	70.00%
4	3	84.48%
4	4	96.74%
5	0	1.43%
5	1	7.30%
5	2	30.00%
5	3	70.00%
5	4	92.70%
5	5	98.57%
6	0	0.62%
6	1	3.26%
6	2	15.52%
6	3	50.00%
6	4	84.48%
6	5	96.74%
6	6	99.38%
7	0	0.26%
7	1	1.43%
7	2	7.30%
7	3	30.00%
7	4	70.00%
7	5	92.70%
7	6	98.57%
7	7	99.74%
8	0	0.11%
8	1	0.62%
8	2	3.26%
8	3	15.52%
8	4	50.00%
8	5	84.48%
8	6	96.74%
8	7	99.38%
8	8	99.89%