Information Partitioning, Learning, and Beliefs*

Pascal Kieren[†] Lukas Mertes[‡] Martin Weber[§]

May 31, 2025

ABSTRACT

We experimentally study how information partitioning affects learning and beliefs. Holding the informational content constant, we show that observing small pieces of information at higher frequency (narrow brackets) causes beliefs to become overly sensitive to recent signals compared to observing larger pieces of information at lower frequency (broad brackets). As a result, partitioning information in narrow or broad brackets causally affects judgements. Observing information in narrow brackets leads to less accurate beliefs and to worse recall than observing information in broad brackets. As mechanism, we provide direct evidence that partitioning information into narrower brackets shifts attention from the macro-level to the micro-level, which leads people to overweight recent signals when forming beliefs.

Keywords: biased beliefs, information bracketing, learning

JEL Classifications: D9, D12, G4

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* We are grateful to Peter Bossaerts, Sam Hartzmark, Camelia Kuhnen, Suk Lee, Emanuel Renkl, Michael Thaler, Stefan Trautmann, Giovanni Trebbi, and Georg von Weizsäcker for helpful comments and discussion. We also thank participants of the FIRS, the AFA, the SJDM, the DGF, the SAFE Household Finance Workshop, the Maastricht Behavioral and Experimental Economics Symposium, the Experimental Finance Conference, the Boulder Summer Conference on Consumer Financial Decision Making as well as seminar participants at the University of Mannheim. Pascal Kieren gratefully acknowledges financial support by the German Research Foundation (DFG) under the grant number 544579747.

† University of Heidelberg, pascal.kieren@awi.uni-heidelberg.de.

‡ University of Mannheim, lukas.mertes@uni-mannheim.de.

§ University of Mannheim and CEPR, London, weber@uni-mannheim.de.

1 Introduction

When evaluating services, goods, or assets, individuals may seek out information to judge whether certain desired characteristics are satisfied. While gathering information, both individuals and information providers can decide how much information to consult or to display at any one time. For instance, consider a prospective investor who gathers information about a company or a consumer who reviews product ratings for a particular good. Sometimes, we review (or obtain) the available information sequentially and in small amounts whereas at other times we review all available information at once. Generally speaking, is it possible that grouping individual information signals into smaller or larger partitions has an effect on learning and beliefs? Bayes' Theorem would prescribe that the partitioning of information should not influence beliefs. However, whether this is the case is ultimately an empirical question.

Taking this observation as a point of departure, this article studies whether information partitioning has a causal influence on investors' learning and beliefs. While the influence of partitioning is well-documented in choice (e.g., Read et al., 1999; Ellis and Freeman, 2024), its implications have not been studied for the formation of expectations. Using four preregistered experimental studies, we show that partitioning information into narrower or broader brackets has a significant influence on how people incorporate such information into their expectations.

In order to identify the causal effect of information partitioning on learning, we designed a setting in which the frequency of observing new information can be exogenously assigned, beliefs can be cleanly elicited, and a normative benchmark for learning can be established. Subjects repeatedly observe signals – framed as price movements – to learn about the quality of a risky asset. Subjects know that the asset has a fixed probability of a price increase in each period, which we refer to as its fundamental quality. As such, a price increase (decrease) corresponds to a positive (negative) signal about the asset's quality. Subjects' task is to infer the quality of the risky asset from the price path, i.e., the asset's price movements over 50 periods. The key component of our study is whether the elicited beliefs depend on how information is partitioned.

In our experiments we exogenously vary the frequency at which subjects observe new information. In the narrow information treatment, subjects observe how the price path builds over time and we elicit subjects' beliefs about the asset's fundamental quality every 10 periods. This treatment aims to elicit beliefs when information arrives in small amounts at higher frequency. In the broad information treatment, subjects observe the entire price path at once and we elicit subjects' beliefs only after period 50. This treatment aims to elicit beliefs when information arrives in large amounts at lower frequency. In our experiments, we have direct control over objective expectations and can compare them to subjects' subjective beliefs. Importantly, a Bayesian agent in our setting would provide an identical posterior belief after the final period irrespective of the frequency of observed information. This allows us to document systematic errors in the belief formation process which we can directly attribute to the partitioning of information.

Our findings can be summarized as follows. We find that partitioning information into narrower or broader brackets significantly influences how individuals incorporate such information into their expectations. Most importantly, observing information in small amounts at higher frequency leads to greater estimation errors (i.e., less precise beliefs) relative to observing the same information in large amounts at lower frequency. The difference in estimation errors is not only statistically highly significant, but also sizable, as estimation errors are on average 28% greater when information is observed at higher frequency relative to lower frequency. To understand why beliefs become less precise when information is observed at higher frequency, we investigate the formation of subjects' beliefs more closely. We show that partitioning information into narrower brackets causes individuals to overweight more recent information and to underweight more distant information. The observed belief movement when information arrives at small amounts at higher frequency can thus be broadly reconciled with diagnostic expectations (Bordalo et al., 2018, 2019) or with the notion that individuals learn with gradually fading memory (Malmendier and Nagel, 2016; Nagel and Xu, 2022). Under diagnostic expectations, individuals on average adjust their beliefs in the right direction but overweight more recent information, while under learning with fading memory, individuals increasingly underweight more distant information. Conversely, we show that partitioning information into broader brackets causes individuals to evaluate information jointly and to put more equal weight on all available information.

Next, we aim to provide evidence on the psychological microfoundation. We conjecture that observing smaller bits of information at higher frequency shifts attention from the macro-level to the micro-level. This heightened attention to small and frequent information signals causes beliefs to become overly sensitive to recent information which leads to overextrapolation from such information. To establish attention as mechanism we proceed in two steps. First, we investigate subjects' memory between the treatments. Attention and memory have an intimate relation as attention determines how information is encoded into memory (Schwartzstein, 2014; Bohren et al., 2024). In line with earlier studies on choice bracketing (Read et al., 1999) we expect that observing information in small amounts at higher frequency (narrow information treatment) causes individuals to selectively focus their attention on small blocks of information, thereby losing sight of the big picture. To analyze the influence of information partitioning on memory, we ask subjects after a random trial a number of questions in which they have to recall some of the encountered information. Consistent with our conjecture, we provide evidence that subjects who observe information at lower frequency are consistently better at recalling past information.

Second, to provide more direct evidence for attention as underlying behavioral mechanism, we conduct an additional experiment, in which we employ techniques from cognitive psychology to exogenously manipulate attention in the narrow information treatment (Verghese, 2001; Mrkva and Van Boven, 2017). Specifically, before reporting their final estimate, participants have to watch the entire price path rebuild and have to identify the price of the asset for five randomly selected periods. Importantly, this manipulation does not provide any new information for participants. However, it allows us to look at whether information partitioning influences the allocation of attention and whether shifting attention away from the micro-level (i.e., individual price changes) to the macro-level (i.e., the entire price path) diminishes the observed gap in beliefs. Consistent with this conjecture, we show that our attention manipulation almost fully closes the gap in beliefs between the narrow and the broad information treatment observed in our baseline experiment. Beliefs are not only less influenced by recent information, but subjects also recall the provided information better and provide much more accurate beliefs. The attention manipulation thus shows that attention is a key driver of the information partitioning effect.

Finally, we explore the influence of information partitioning in two specific applications. We first focus on a finance context in which more recent information is arguably also more informative. If that is the case, observing information in narrow brackets - and hence overweighting recent information - may result in better calibrated beliefs. We test this conjecture in a third experiment on an investor sample. Importantly, the experiment employs a data-generating process governed by a Markov chain that leads a Bayesian agent to overweight more recent information. In line with the information partitioning effect documented in our baseline experiments, subjects in the narrow treatment now indeed provide more accurate beliefs as they put more weight on more recent information than subjects in the broad treatment. We then turn to a consumer choice application, in which customers judge the quality of good based on online reviews. In contrast to our baseline experiments, such a setting features more qualitative information, and is not about probabilistic beliefs but the perceived quality of a good. We conduct a fourth experiment in which subjects learn about a fictional smartphone based on product ratings to investigate the information partitioning effect in the consumer choice context. As before, subjects in the narrow treatment put more weight on recently observed information, while subjects in the broad treatment put more weight on the aggregate information and less weight on recent information. Overall, these applications demonstrate that our results are highly consistent across information type (qualitative vs. quantitative), setting (financial markets vs. online market places), and data-generating processes (equal-weighted information signals vs. Markov chain).

Our findings add to the literature on behavioral biases in belief formation, as recently reviewed in Benjamin (2019). Prior research shows that people tend to neglect base-rates (Kahneman and Tversky, 1973; Fischhoff and Bar-Hillel, 1984), display overconfidence (Moore and Healy, 2008), do not sufficiently account for correlations in the data-generating process (Enke and Zimmermann, 2019; Ungeheuer and Weber, 2021), sometimes overinfer (Bordalo et al., 2018, 2020; Hartzmark et al., 2021; Kieren et al., 2022), and sometimes underinfer from recent signals (Edwards and Phillips, 1964; Phillips and Edwards, 1966). More recent research also investigates how heterogeneity in the learning environment can affect the belief formation process. Ba et al. (2022) and Augenblick et al. (2021) show that people overreact to information in complex and noisy environments, while they underreact in simple environments. Bohren et al. (2024) show that learning differs depending on whether information is acquired from descriptions or from sequential sampling. In a similar spirit, our main emphasis is not on the type of information being provided. Instead, we are interested in whether partitioning the same information into narrower or broader brackets affects judgement. An important conceptual question in sequential belief updating is how individuals group signals (Benjamin et al., 2016). For instance, if people are assumed to treat signals which they observe as distinct samples, they would update their beliefs after each signal and their updated belief after the first signal would subsequently become their prior when updating in response to the next signal. Alternatively, if people are assumed to pool all signals they have observed up until a certain point, they would always update from their initial prior using the updated pooled sample. As argued by Benjamin et al. (2016), differences in grouping can be a mechanism behind dynamically inconsistent behavior[1]. Despite its importance, only a few studies have touched upon that question so far (Benjamin, 2019). Our results show that neither of the two assumptions regarding information grouping can be considered a universal feature of information processing. Instead, people group outcomes differently depending on how the presented information is partitioned.

We also contribute to recent work studying the role of memory in belief formation. For example, Enke et al. (2020) show that people selectively recall pieces of information from the past if the context in which it is experienced is similar to today's context. Consistent with this notion, an increasing number of studies argues that selective recall of information might be a potential mechanism for self-servingly biased beliefs (e.g., Bénabou and Tirole, 2002; Chew et al., 2020; Zimmermann, 2020). In contrast to the notion that "losses loom larger than gains" in choices under risk (Kahneman and Tversky, 1979), individuals seem to fail to update fully in response to negative news when motivation is at play (Bénabou and

[1] He and Xiao (2017) even show that assumptions on how people group signals will matter for *any* non-Bayesian updating rule.

Tirole, 2016). Applied to investment decisions, Gödker et al. (2021) show that individuals tend to over-remember positive investment outcomes and under-remember negative ones. Jiang et al. (2023) find that investors are more likely to remember market episodes which are more similar to current market returns. Our study differs in that we do not focus on the type of information that is being remembered (i.e., "good news" versus "bad news") but rather on how the frequency and the partitioning of information makes information more or less memorable. This has important implications for the understanding of how people learn from their experiences. In particular, learning from information which arrives in large amounts at lower frequency appears to foster good memory about the provided information. Conversely, learning from frequent small bits of information leads to significantly worse memory consistent with the notion of people losing sight of the trees for the forest (Jacobs and Weber, 2016).

Finally, our study relates to the literature on information aggregation and myopic loss aversion. Early experimental evidence shows that subjects are less risk-averse when they observe returns less frequently but aggregatedly or over long-term (rather than short-term) horizons (Gneezy and Potters, 1997; Benartzi and Thaler, 1999). Similarly, repeated lotteries are perceived as less risky as the number of repetitions increases (Klos et al., 2005). More recently, Beshears et al. (2017) aim to resemble a more realistic setting by having subjects invest in real financial assets over the course of a year and do not find that information aggregation affects risk-taking. Leveraging a regulatory change in Israel, which required retirement funds to display returns over periods of at least twelve months instead of one month, Shaton (2017) provides evidence for myopic loss aversion in the real world. Following the change, investments in riskier retirement funds increased and fund flows became less sensitive to past 1-month returns. While we examine the influence of the frequency at which information is observed, our study is distinct in that individual information is not aggregated. Instead of observing a 12-month return, subjects in our experiments observe twelve 1-month returns, either sequentially or at once. Our findings imply that not only the aggregation of information, but also the frequency at which *individual* information is observed affect (risk-taking) behavior.

2 Conceptual Framework

Suppose in each period t, a good (or service) generates a binary signal $s_t \in \{g, b\}$. Signals in all periods are i.i.d., and the full history of observed signals until period t is represented by $S_t = (s_1, s_2, \dots, s_t)$. In financial markets, signals can be thought of as earnings surprises or dividends, whereas in consumer markets, signals can be thought of as quality signals. Which signal is generated in a given period depends on the good's underlying type. The agents' task is to observe the signals and to make inferences about the good's underlying type. The good can either be a good or a bad type, represented by G and B, respectively. Each type corresponds to an underlying distribution from which signals are generated. The probability of observing signal g is θ_G for a good type, and θ_B for a bad type, with $0 < \theta_B < \theta_G < 1$. If signals are ordered outcomes (with good outcomes being preferred over bad outcomes), this implies that the good type has a signal distribution that first-order stochastically dominates the bad type. Let π_0^G and π_0^B represent the agent's prior belief about the good and bad type, respectively.

Following Gabaix (2019) and Enke and Graeber (2023), we assume that agents form beliefs based on a convex combination of their prior belief and the (Bayesian) posterior belief implied by the observed signal:

$$\pi_t^G(S_t) = (1-\lambda)\pi_{t-1}^G + \lambda \mu_t^G \tag{1}$$

with

$$\mu_t^G(S_t) = \frac{P(s_t \mid \theta_G)\pi_{t-1}^G}{\sum_{j=G,B} P(s_t \mid \theta_j)\pi_{t-1}^j}, \tag{2}$$

where $\pi_t^G(S_t)$ denotes the agent's posterior belief that the good's type is G conditional on the observed signal history S_t, π_{t-1}^G is the agent's prior belief in period $t-1$, μ_t^G is the posterior implied by the signal, $P(s_t \mid \theta_j)$ is the probability of observing signal s_t conditional on the type $j \in \{G, B\}$, and $\lambda \geq 0$ represents the relative weight placed on the posterior implied by the observed signal. This model preserves the martingale property of the Bayesian posteriors. It nests Bayesian updating for $\lambda = 1$. Choosing $\lambda < 1$ allows the agent to underinfer from new information, whereas $\lambda > 1$ allows the agent to overinfer. As such, λ permits a variety of belief updates ranging from extreme dogmatism ($\lambda = 0$), where the agent entirely relies on their initial belief, to jumping to certainty ($\lambda \to (1 - \pi^G_{t-1})(\mu^G_t - \pi^G_{t-1})^{-1}$). The resulting updating process is comparable with an anchoring-and-adjustment heuristic (Tversky and Kahneman, 1974), in which individuals anchor their estimates on some initial belief and then adjust it in the direction of the observed information.

Next, assume that agents observe signals in batches of size $n \in \{1, 2, \dots\}$. Importantly, the good continues to generate a signal in each period t. However, agents may not observe the signal in each period. This could either be due to attentional constraints or by deliberation. We denote the ordered set of signals that an agent observes in any period t by $s_{t:n} \equiv \{g_x, b_y\}^n$, where g_x and b_y denote the number of g and b signals contained in the batch, with $x + y = n$, and n denotes the size of the batch. Note that when an agent observes signal batch $s_{t:n}$ in period t, this implies that the last signal batch must have been observed in period $t - n$. As signals continue to be i.i.d., it follows that:

$$P(s_{t:n} \mid \theta_j) = \prod_{i=0}^{n-1} P(s_{t-i} \mid \theta_j). \tag{3}$$

We now consider how the agent's beliefs evolve over t periods under different assumptions regarding how information is incorporated into beliefs.

Narrow Information Processing. First, assume that information is observed at higher frequencies. The limit case is $n = 1$. We call this *narrow information processing.* If information is processed in narrow batches of size 1, the agent iterates the updating process described in Equation (1) and (2) for each of the t periods:

$$\pi_t^{G,\text{narrow}}(S_t) = (1 - \lambda)\pi_{t-1}^{G,\text{narrow}} + \lambda\mu_t^{G,\text{narrow}}, \tag{4}$$

with

$$\mu_t^{G,\text{narrow}}(S_t) = \frac{P(s_t \mid \theta_G)\pi_{t-1}^{G,\text{narrow}}}{\sum_{j=G,B} P(s_t \mid \theta_j)\pi_{t-1}^{j,\text{narrow}}}. \tag{5}$$

This updating procedure is the standard assumption in many models of rational belief updating, as new information is immediately incorporated into prior beliefs.

Broad Information Processing. Alternatively, assume that information is observed at lower frequencies in batches of size $n > 1$. We call this *broad information processing.* Since individuals cannot perform intermediate belief updates when observing information in batches, they perform a single belief update based on the prior they had in period $t - n$. Hence, the updating protocol is:

$$\pi_t^{G,\text{broad}}(S_t) = (1 - \lambda)\pi_{t-n}^{G,\text{broad}} + \lambda\mu_t^{G,\text{broad}}, \tag{6}$$

with

$$\mu_t^{G,\text{broad}}(S_t) = \frac{P(s_{t:n} \mid \theta_G)\pi_{t-n}^{G,\text{broad}}}{\sum_{j=G,B} P(s_{t:n} \mid \theta_j)\pi_{t-n}^{j,\text{broad}}}, \tag{7}$$

where $P(s_{t:n} \mid \theta_j)$ is the probability of observing batch $s_{t:n}$ conditional on the type $j \in \{G, B\}$ and π_{t-n}^G is the agent's prior belief before observing the most recent batch in period $t - n$.

Note that the two updating processes outlined above require a different kind of mental agility when updating beliefs. If information arrives in narrow batches, agents must put substantially more effort into updating beliefs (as they update more frequently) but require less memory as they do not need to keep track of all previous signals. In fact, the current belief π_{t-1}^G and the most recent signal s_t are sufficient to know. If information arrives in broad batches, individuals update less frequently but must incorporate all n signals of the most recent batch into their prior belief from period $t - n$, which requires more memory capacity.

Most importantly, the two updating procedures result in different posterior beliefs, $\pi_t^{G,\text{narrow}} \neq \pi_t^{G,\text{broad}}$, despite observing the same signals up until period t. The only exception is when $\lambda = 1$, i.e. belief updating is Bayesian (see Cripps, 2018; for a related discussion).

3 Experimental Design

3.1 Baseline Design

In order to examine the causal effect of information partitioning on learning and beliefs we require a setting with the following features: (1) individuals repeatedly incorporate new information signals into their beliefs; (2) the frequency at which individuals observe new information can be exogenously assigned; (3) beliefs can be compared to a normative benchmark; and (4) the belief elicitation is incentive-compatible. We design four preregistered experiments to accommodate these features.

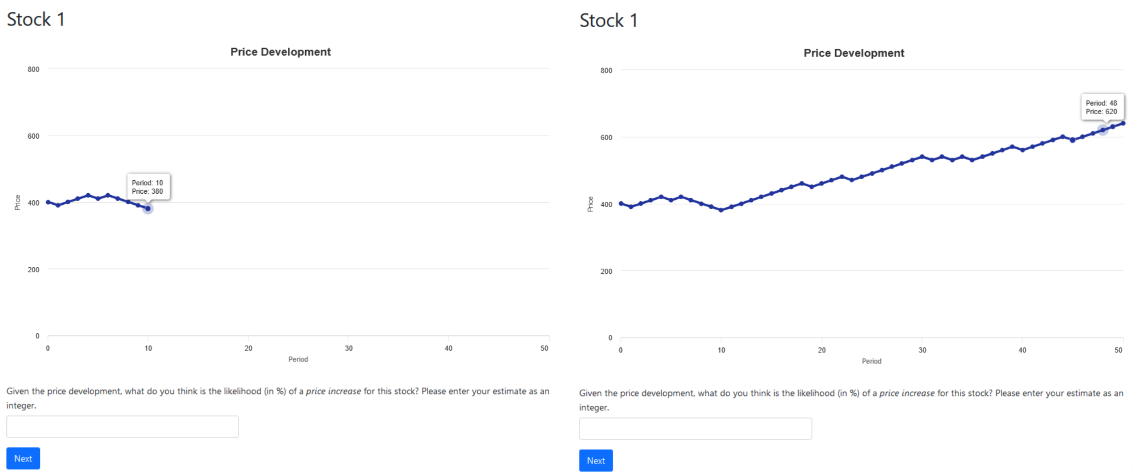
In this section, we outline the features of our baseline experiment (Experiment 1) in detail. In the experiment, subjects have to form beliefs about the fundamental quality of a risky asset. The asset has a fixed probability of a price increase, $s^i \in \{0.20, 0.21, ..., 0.80\}$, which represents its fundamental quality. The asset starts with an initial price of 400. In each period $t \in \{1, 2, ..., 50\}$, the price level of the asset either increases or decreases by a constant amount; a price increase is always 10 and a price decrease is always -10. In every period, the current and prior price levels are provided to subjects in a price-line chart. Since a price increase is more likely to be observed if the risky asset has a higher fundamental quality s^i, price changes correspond to signals about the asset's fundamental quality.

Subjects are informed that the risky asset has a fixed fundamental quality between 20% and 80%, but are not informed about the actual quality. Their task is to infer this quality from the observed price changes. Specifically, we ask subjects to report their belief p^i regarding the probability of a price increase of the risky asset. Subjects record their beliefs using a slider ranging from 20% to 80% in 1 percentage points increments. The key component of our study is whether the elicited beliefs regarding the fundamental quality depends on how information is partitioned. We introduce two between-subject treatments for eliciting beliefs at different frequency, termed *narrow information* and *broad information.*

In the *narrow information* treatment, we elicit subjects' beliefs about the asset's fundamental quality every 10 periods. This treatment aims to elicit beliefs when information arrives in small amounts at higher frequency. Subjects start with an empty price-line chart at period $t = 0$ which *builds* over time, reflecting the notion that small bits of information arrive at higher frequency. Once they are ready to begin with the task, they observe a price change every 0.5 seconds until they observe a total of 10 price changes, i.e., until period 10. Afterwards, we elicit their beliefs about the asset's fundamental quality (Figure 1a). This process then continues in batches of 10 periods until subjects reach period 50, leading to a total of five estimates.

In the *broad information* treatment, we elicit subjects' beliefs about the asset's fundamental quality only once. This treatment aims to elicit beliefs when information arrives in large amounts at lower frequency. Similar to before, subjects start with an empty price-line chart at period $t = 0$. In contrast to the *narrow information* treatment, however, the graph does not build over time. Once subjects are ready to begin, they observe all price changes between period 1 and 50 at once. Afterwards, we elicit their beliefs about the asset's fundamental quality (Figure 1b).

Figure 1: Experiment 1: Treatments



(a) Narrow Information **(b)** Broad Information

Note: This figure presents exemplary screens of the estimation task as seen by subjects in Experiment 1. In the narrow information treatment (a), the price-line chart builds over time and subjects beliefs about the asset's fundamental are elicited every 10 periods. In the broad information treatment (b), subjects observe all price changes between period 1 and 50 at once and their beliefs are only elicited in period 50.

Overall, subjects play multiple trials each consisting of 50 periods. The fundamental quality of a risky asset is only fixed for one particular trial and as such varies across trials.

This information is known to subjects. To account for the fact that subjects in the broad information treatment make fewer choices than those in the narrow information treatment, the former will complete eight trials (with 50 rounds each) while the latter only complete four trials (with 50 rounds each). The experiment concludes with a brief survey about subjects' socioeconomic background.

To analyze the influence of information partitioning on beliefs, it is crucial for our experimental design that subjects between treatments have access to the same information. We address this in two ways. First, our main variable of interest is subjects' reported belief about the fundamental quality of the risky asset in period 50. This ensures that the available information set at the time of the decision is identical and allows to attribute any observed difference in beliefs to our treatments. Second, we follow convention in randomly generating the price paths before the experiment (e.g., Hartzmark et al., 2021; Fischbacher et al., 2017). This not only facilitates between-subject analyses but also allows enables direct comparison of beliefs between treatments conditional on observing the same information. We first randomly drew 4 price paths for fundamental qualities greater than 50% ("positive paths" hereafter). Next, for each price path we rotated price changes to create variation in observed price path patterns without affecting the final price (and thus increasing statistical power without changing the final Bayesian posterior). This way, we generated a total of 12 price paths with fundamental qualities greater than 50%. Finally, we mirrored each price path to obtain another 12 price paths for fundamental qualities of less than 50% ("negative paths" hereafter). This allows us to detect potential asymmetries between increasing and decreasing price paths, leading to a total of 24 price paths.

Subjects are incentivized based on the accuracy of their estimates. At the end of the experiment, we randomly select three estimates. For each selected estimate p^i that is within plus or minus 5 percentage points of the true probability of a price increase, s^i, subjects receive a bonus of £0.3. Additionally, subjects receive a fixed participation fee of £1.25. We chose this incentivization mechanism for its simplicity by imposing fewer cognitive burdens on subjects. Overall, this creates a simple and transparent learning environment which fosters truthful reporting as the number of price increases and decreases are a sufficient statistic for calculating the posterior probability which we incentivize. In contrast, recent studies show that more complex incentivization schemes such as the Binarized Scoring Rule (or variations such as the Quadratic Scoring Rule) can systematically bias truthful reporting, resulting in greater errors rates relative to simpler mechanisms (Danz et al., 2022).

In addition to the estimation task, we add a memory elicitation task in the spirit of Gödker et al. (2021) to control the influence of our treatments on subjects' memory. The memory elicitation consists of a number of questions in which subjects have to recall specific outcomes of the risky asset which they learn about. Specifically, we ask subjects to recall how many positive and negative price changes they observed, the final price after period 50, as well as the maximum streak length of subsequent positive respectively negative price changes. The memory task always occurs after either the first or the last trial of an experiment in a counterbalanced order. The memory task is not announced beforehand and subjects no longer have access to the price-line chart. We aggregate the number of correctly recalled questions to an overall memory score ranging from 0 (none of the five questions was answered correctly) to 5 (all questions were answered correctly). The memory task is incentivized in addition to the estimates. Subjects receive £0.1 for each correctly recalled question.

3.2 Recruitment Procedure

The experiment was computerized using oTree (Chen et al., 2016). We recruited a total of 3,059 individuals ($N = 713$ for Experiment 1) from the crowdsourcing platform Prolific to participate in four experiments. The design, hypothesis, and sample selection criteria are all preregistered[2]. The study obtained ethics approval by the Institutional Review Board of the authors' institution. The subject pool is comprised of subjects from the UK and the US.

[2] The preregistration documents can be found at `https://aspredicted.org/LJ1_GZ3` (Experiment 1), `https://aspredicted.org/DJP_5ZZ` (Experiment 2), `https://aspredicted.org/rp22-jwdt.pdf` (Experiment 3), and `https://aspredicted.org/jhf2-wk5x.pdf` (Experiment 4).

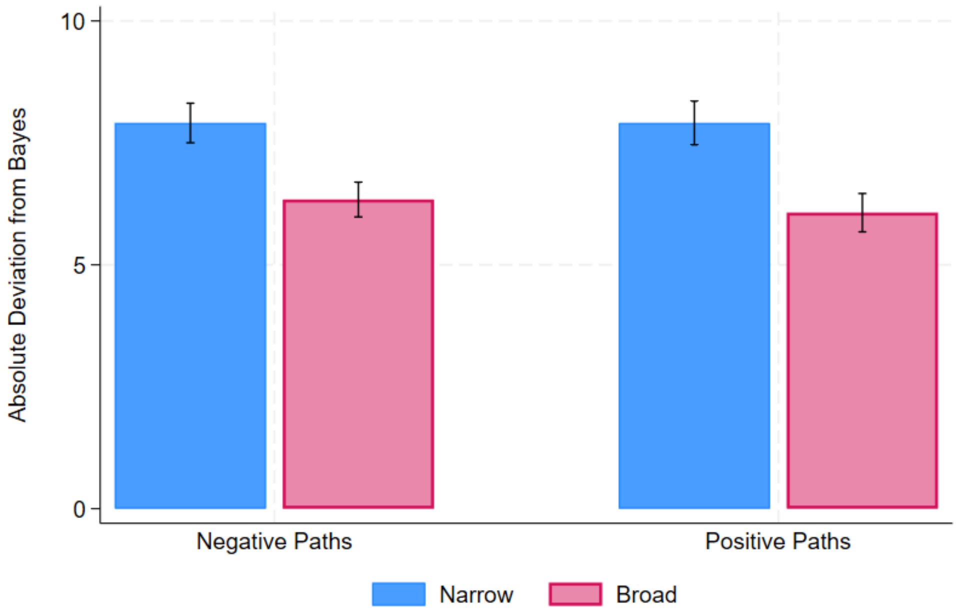
4 Results

4.1 Information Partitioning and Learning

Accuracy of Beliefs

To assess the influence of information partitioning on beliefs, we first compare subjects' estimation error, computed as the absolute difference between reported beliefs p^i and Bayesian beliefs b^i in period 50, between the narrow and broad information treatments. If information partitioning does not affect beliefs, there should be no difference in estimation error between treatments. Figure 2 plots the average estimation error for each treatment, split by positive (i.e., upward-trending) and negative (i.e., downward-trending) price paths.

Figure 2: Experiment 1: Estimation Error



Note: This figure plots the average estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) per treatment in Experiment 1 for negative respectively positive price paths.

First, note that irrespective of whether the price path was increasing or decreasing, the estimation error in the in narrow information treatment (blue bars) is significantly higher than the estimation error in the broad information treatment (red bars). For negative price paths, the estimation error in the narrow treatment is 7.9 percentage points, while the estimation error in the broad treatment is 6.3 percentage points, leading to a difference of 1.6 percentage points ($p < 0.001$). For positive price paths, the estimation error in the narrow treatment is also 7.9 percentage points, while the estimation error in the broad treatment is 6.1 percentage points, leading to a difference of 1.8 percentage points ($p < 0.001$). In relative terms, this implies that observing information at higher frequency leads to estimation errors which are on average 25% and 30% higher relative to observing information at lower frequency.

While the pattern in Figure 2 provides first insights on the influence of information partitioning on beliefs, we test the following regression model to account for the dependence of observations:

$$|Estimate_i - Bayes_i| = \alpha + \beta_1 Bayes_i + \beta_2 Narrow_i + \epsilon_i$$

We regress subjects' estimation error after having observed all information on the Bayesian posterior and a narrow information dummy, which equals 1 if a subject is in the narrow information treatment and 0 otherwise.

Table 1: Experiment 1: Estimation Error

	Overall	Overall	Negative	Positive
bayes	-0.07	-0.09	0.25^{***}	-0.13^{***}
	(0.00)	(0.00)	(0.04)	(0.04)
narrow	1.70^{***}	1.67^{***}	1.51^{***}	1.82^{***}
	(0.29)	(0.28)	(0.33)	(0.37)
Controls	No	Yes	Yes	Yes
N	3,700	3,656	1,851	1,805
R^2	0.02	0.04	0.06	0.05

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 1 presents the results estimated on the whole sample (Columns (1) and (2)), as well as for positive and negative price paths separately (Columns (3) and (4), respectively). Across all specifications, the coefficient of $Narrow$ is positive and highly statistically significant ($p < 0.001$), suggesting that observing information at higher frequency on average leads to greater estimation errors. Consistent with the graphical evidence presented in Figure 2, this suggests that partitioning information into narrower or broader brackets has a significant influence on the accuracy of individuals' expectations.

Information Weights and Belief Formation

To obtain a better understanding of why subjects in the narrow information treatment report less accurate beliefs despite observing the same information, we investigate subjects' reaction to the provided information more closely. Specifically, we examine whether partitioning information into narrower or broader brackets affects how subjects weigh information brackets when forming their beliefs. Since subjects in the broad treatment receive all information at once (one large bracket) and subjects in the narrow treatment receive information in five brackets of 10 signals, we estimate the weight attached to all information versus the last observed bracket. To do so, we run the following regression:

$$\begin{aligned} Estimate_i = \alpha + \beta_1 Narrow_i + \beta_2 All_i + \beta_3 All_i * Narrow_i \\ + \beta_4 Last_i + \beta_5 Last_i * Narrow_i + \epsilon_i \end{aligned} \tag{8}$$

We regress subjects' final posterior belief p^i in round 50 on the $Narrow$ dummy, as well as on two variables, All_i and $Last_i$, that both capture blocks of information, and their interaction with the treatment dummy. All_i corresponds to information observed over all 50 periods, while $Last_i$ corresponds to information observed over the last 10 periods. In Columns (1) and (2) of Table 2, All_i ($Last_{it}$) is defined as the change in Bayesian beliefs between period 0 and 50 (40 and 50). In Columns (3) and (4), All_i ($Last_i$) is defined as the risky asset's change in price between period 0 and 50 (40 and 50)[3].

As can be inferred, both more distant as well as more recent information influence subjects' final posterior belief in both treatments. Notice that our design does not favor more recent information. Instead, a Bayesian would put equal weight on all encountered signals. However, regardless of whether the informational content is measured by the change in Bayesian beliefs or by price changes, subjects in the narrow treatment put less weight on more distant

[3] Table A2 in Appendix B additionally includes control variables and displays similar results.

Table 2: Experiment 1: Beliefs

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.37	omitted	-0.37	omitted
	(0.35)		(0.36)	
all	0.98***	0.99***	0.08***	0.08***
	(0.01)	(0.01)	(0.00)	(0.00)
all × *narrow*	-0.06***	-0.07***	-0.02***	-0.02***
	(0.02)	(0.02)	(0.00)	(0.00)
last	0.13*	0.13*	0.02***	0.01***
	(0.07)	(0.07)	(0.01)	(0.01)
last × *narrow*	0.83***	0.88***	0.07***	0.08***
	(0.11)	(0.12)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	3,700	3,700	3,700	3,700
R^2	0.83	0.83	0.83	0.83

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables. In columns (1) and (2), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 50 (40 and 50). In columns (3) and (4), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

observations ($p < 0.001$) and more weight on recent information ($p < 0.001$) than subjects in the broad treatment. In other words, partitioning information into narrower brackets causes individuals to overweight more recently observed information brackets and to underweight more distant information when forming beliefs. Importantly, this pattern is not limited to only the last information bracket. In Table A3 in Appendix B, we report alternative specifications that consistently show that subjects in the narrow treatment assign disproportionate weight to more recent information brackets, while subjects in the broad treatment assign more equal weight to all available information.

4.2 Exploring the Mechanism

The previous section demonstrates that partitioning information into narrower or broader brackets influences learning and beliefs. In this section, we aim to provide evidence for a specific mechanism behind the effect. Note that the belief partitioning effect is not consistent with Bayesian learning which predicts no difference depending on how information is partitioned.

Additionally, the effect is not consistent with models of motivated beliefs (e.g., Kunda, 1990; Brunnermeier and Parker, 2005) or misattribution (e.g., Ross, 1977; Gagnon-Bartsch and Bushong, 2022) which predict differences based on how desirable information is but not depending on how the same information is partitioned, or models of recency bias (e.g., Camerer and Hua Ho, 1999; Fudenberg et al., 2014) which predict no difference as the most recent information is identical across treatments. Finally, since our results are robust to the inclusion of subject fixed effects, the belief partitioning effect cannot be explained by heterogeneity based on fixed participant characteristics.

We now consider a mechanism under which partitioning information into narrower brackets shifts attention from the macro-level (i.e., the information as a whole) to the micro-level (i.e., individual pieces of information). This heightened attention to small and frequent information signals causes belief movement to become overly sensitive, which leads to the overweighting of individual information brackets in the narrow treatment. The conjecture that increased attention to individual information fosters greater overreaction is supported by recent studies in economics and cognitive psychology. For instance, Hartzmark et al. (2021) show that ownership channels attention towards signals associated with owned goods which leads to over-extrapolation from such signals. Additionally, over-extrapolation is at least partly driven by the associative nature of memory through recall when making judgements (e.g., Gennaioli and Shleifer, 2010; Bordalo et al., 2020; Enke et al., 2020). For example, Enke et al. (2020) show that people overreact to information because they are more likely to recall similar prior information.

Prior work has shown that attention and memory have an intimate relation. Before a signal can be recalled, it must first be encoded into memory. In fact, attention determines what type of information is encoded into memory (Schwartzstein, 2014; Hartzmark et al., 2021; Bohren et al., 2024). If partitioning information into narrower or broader brackets affects attention and thus determines which signals are encoded into memory, then the cognitive process outlined above generates testable hypotheses on comparative statics between the partitioning of information and individuals' beliefs and memory. We conjecture that – in the spirit of choice bracketing (e.g. Read et al., 1999) – observing information at lower frequency (narrow information treatment) causes individuals to selectively focus their attention on small blocks of information, thereby losing sight of the big picture. As a result, beliefs become overly sensitive to recent information. We therefore expect that excessive attention to the micro-level leads to worse memory at the macro-level, which eventually causes beliefs to be further away from the Bayesian benchmark.

Information Partitioning and Memory

To test the mechanism outlined above, we first investigate whether partitioning information into narrower or broader brackets influences how memorable the observed information is. If subjects in the broad information treatment pay more attention to information at the macro-level (i.e., they pay equal attention to all information brackets) than subjects in the narrow information treatment, they should answer more memory questions correctly.

Table 3 displays subjects' answers to the memory questions elicited in the baseline experiment. Panel A shows the fraction of subjects who answered the respective question correctly. Across questions and treatments approximately 17% of questions were answered correctly. When the questions ask for the number of increases, the number of decreases or the final price, the fraction answered correctly is significantly higher in the broad information treatment than in the narrow information treatment. The differences are sizable as share of correct answers in the broad information treatment are roughly 50% higher than in the narrow information treatment. There is no difference between treatments for the questions about the maximum streak length of increases and decreases. Comparing the number of correctly answered questions reveals a similar pattern (Panel B).

Our memory analysis shows that subjects in the broad information treatment exhibit a better recall than those in the narrow information treatment, which is in line with subjects in the broad information treatment paying more attention to the macro-level than subjects in the narrow information treatment. Next, we investigate the transmission of memory on the formation of beliefs, by regressing subjects' estimation error on their memory score, i.e., the number of correctly answered memory questions. Table 4 displays results for the whole sample (Column 1), the whole sample with a treatment interaction (Column 2) and for

Table 3: Experiment 1: Memory

Panel A: Fraction	in %		
	Broad	Narrow	Difference
increases	19.81	13.57	6.24**
			(2.11)
decreases	19.81	13.77	6.04**
			(2.03)
final price	25.00	16.37	8.63***
			(2.69)
streak up	16.04	17.96	-1.93
			(0.62)
streak down	17.45	17.17	0.29
			(-0.09)
Panel B: Number			
	Broad	Narrow	Difference
memory score (all 5)	0.98	0.79	0.19*
			(1.83)
memory score (first 3)	0.65	0.44	0.21***
			(3.53)

Note: This table displays answers to the memory questions of Experiment 1. Panel A displays the fraction of subjects who answered correctly per question and by treatment (broad vs. narrow information). Panel B displays the memory score out of all 5 and out of the first 3 questions by treatment. In both panels, the final column presents Mann-Whitney tests for differences in means across treatments; the corresponding z-scores are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

each treatment separately (Columns 3 and 4). All specifications consistently show that the number of correctly answered memory questions is negatively related to the absolute difference between subjective and objective beliefs. In other words, better recall at the macro-level leads to more accurate belief forecasts, consistent with the outlined mechanism. Importantly, the relation is present in both treatments and approximately equal in magnitude, suggesting that although memory differs across treatments, the transmission mechanism of memory on beliefs is not affected by how information is partitioned.

Information Partitioning and Attention

Finally, we aim to provide direct evidence for attention as underlying mechanism behind the belief partitioning effect. We use a comparative static approach to exogenously manipulate attention in the narrow information treatment. If the effects in our baseline experiment

Table 4: Experiment 1: Memory and Accuracy

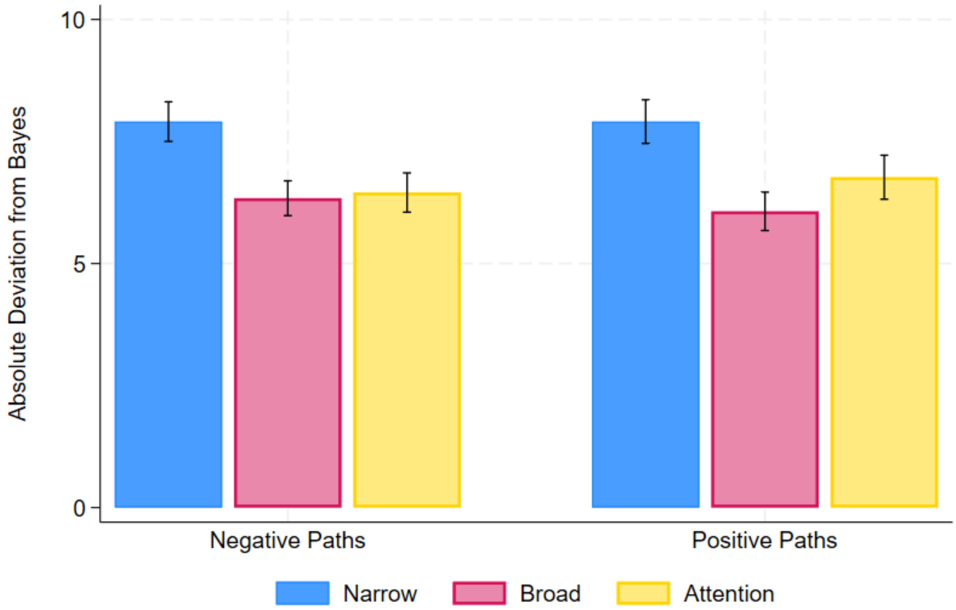
	Overall	Overall	Narrow	Broad
memory score	-0.92***	-0.93***	-0.91***	-0.93***
	(0.11)	(0.15)	(0.17)	(0.16)
narrow	1.53***	1.59***		
	(0.28)	(0.34)		
memory score × *narrow*		0.03		
		(0.23)		
N	3,700	3,700	2,004	1,672
R^2	0.05	0.05	0.02	0.04

Note: This table shows regressions with the absolute deviation of the subjects' beliefs from the Bayesian posterior as dependent variable and the memory score, and control variables as independent variables. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

are driven by differences in attention depending on how information is partitioned, then exogenously manipulating attention in the narrow information treatment should diminish the observed gap in beliefs across treatments. To do this, we conduct an additional experiment (Experiment 2; $N = 352$), which directly builds on our baseline design. As in the narrow information treatment of the baseline experiment, subjects observe a price change every 0.5 seconds and report their beliefs about the asset's fundamental quality every 10 rounds. However, before reporting their final belief in period 50, subjects have to watch the entire price path rebuild and have to identify the price of the asset for five random periods (See Figure B10 in Appendix C.). This method is inspired by prior research in cognitive psychology, which shows that visual search fosters attention (Verghese, 2001; Mrkva and Van Boven, 2017). The periods are randomly drawn such that each 10-period bracket of the price path, i.e., periods 1-10, 11-20, 21-30, 31-40, and 41-50, is covered. The price identification task was incentivized: One trial was randomly selected to determine the bonus payment and subjects received £0.5 if they identified all five prices in this trial correctly. We thereby aim to shift attention away from individual information brackets towards the entire price path. If the attention manipulation is successful, beliefs will move closer to those in the broad information treatment of the baseline experiment.

Figure 3 plots subjects' average estimation error for our attention manipulation (Experiment 2; in yellow) and compares it to the narrow (blue) and broad (red) information treatment from the baseline.

Figure 3: Experiment 2: Estimation Error



Note: This figure plots the average estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) in Experiment 2 in comparison to the narrow and broad information treatment of Experiment 1 for negative respectively positive price paths.

Consistent with the our conjecture, we find that estimation errors in the attention manipulation are significantly lower than those in the narrow treatment of the baseline experiment ($p < 0.01$ for both negative and positive paths). Additionally, we find that estimation errors in the attention manipulation (6.5 and 6.8 for negative and positive price paths, respectively) are now statistically indistinguishable from estimation errors in the broad treatment of our baseline experiment (6.1 and 6.3, for negative and positive price paths, respectively). As such, shifting attention from the micro-level to the macro-level successfully closes the gap between the narrow and the broad information treatment observed in the baseline experiment. Table A4 in Appendix B confirms this in a regression setting.

Next, we investigate whether the attention manipulation affects how subjects weight recent and more distant information when forming their beliefs. Specifically, we run the following regression model:

$$
\begin{aligned}
Estimate_i = \alpha + \beta_1 Attention_i + \beta_2 All_i + \beta_3 All_i * Attention_i \\
+\beta_4 Last_i + \beta_5 Last_i * Attention_i + \epsilon_i
\end{aligned}
\tag{9}
$$

where *Attention* is a dummy that equals 1 if a subject is in the attention manipulation and 0 if a subject is in the narrow information treatment of the baseline experiment. Table 5 presents the results. Compared to subjects in the narrow information treatment of our baseline experiment, subjects in the attention manipulation underweight recent information and overweight more distant information. Attention thus directly affects how information is incorporated into subjects' beliefs.

Table 5: Experiment 2: Beliefs

	$\Delta Bayes$		$\Delta Price$	
	(1)	(2)	(3)	(4)
attention	-0.14	omitted	-0.13	omitted
	(0.35)		(0.35)	
all	0.91^{***}	0.92^{***}	0.07^{***}	0.07^{***}
	(0.01)	(0.01)	(0.00)	(0.00)
all × *attention*	0.11^{***}	0.12^{***}	0.02^{***}	0.02^{***}
	(0.02)	(0.02)	(0.00)	(0.00)
last	0.96^{***}	1.01^{***}	0.09^{***}	0.09^{***}
	(0.09)	(0.00)	(0.01)	(0.01)
last × *attention*	-0.70^{***}	-0.86^{***}	-0.06^{***}	-0.07^{***}
	(0.11)	(0.12)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	3,412	3,412	3,412	3,412
R^2	0.83	0.83	0.82	0.82

Note: This table shows regressions with the final posterior belief as dependent variable and the attention dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables. In columns (1) and (2), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 50 (40 and 50). In columns (3) and (4), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Finally, we use subjects' answers to the memory questions to validate that our manipulation indeed affects attention and ultimately memory. The results of this exercise are reported in Table 6. Panel A shows that the fraction of correct answers in the attention manipulation is higher than in the baseline for each of the 3 questions asked in the attention manipulation[4]. In comparison to the broad information treatment, the differences in fractions are small and not significant, but in comparison to the narrow information treatment the differences are highly significant. The attention manipulation increases the fraction of correct answers in the narrow information treatment by at least 50%, resulting in a level of correct answers which is similar to the one in the broad information treatment. Panel B confirms this impression using the number of correctly answered questions. We conclude that our attention manipulation was indeed successful in shifting subjects' attention towards the entire price path, resulting in a better ability to recall the provided information at the macro-level.

Table 6: Experiment 2: Memory

Panel A: Fraction			in %		
	Attention	Broad	Difference	Narrow	Difference
increases	23.58	19.81	3.77	13.57	10.01***
			(1.04)		(3.77)
decreases	23.58	19.81	3.77	13.77	9.81***
			(1.04)		(3.68)
final price	24.15	25.00	-0.85	16.37	7.78***
			(-0.23)		(2.82)
Panel B: Number					
	Attention	Broad	Difference	Narrow	Difference
memory score	0.71	0.65	0.07	0.44	0.28***
			(0.58)		(4.68)

Note: This table displays answers to the memory questions of Experiment 2 in comparison to the broad respectively narrow information treatment of Experiment 1. Panel A displays the fraction of subjects who answered correctly per question and Panel B displays the memory score out of all 3 questions asked in Experiment 2. In both panels, Mann-Whitney tests are used to test for differences in means; the corresponding z-scores are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

5 Applications

In this section, we explore applications of the influence of information partitioning on the formation of beliefs. We first study an application to financial markets in which more recent

[4] In comparison to the baseline experiment, the recall task in the attention manipulation only comprises the questions regarding the number of positive and negative price changes, as well as the final price in period 50.

information carries greater value than older information. Second, we study an application to consumer choice, in which customers judge the quality of a good based on online reviews.

5.1 Financial Markets

One of the basic premises in financial economics is that market prices are very informative about the fundamentals of traded assets (Goldstein, 2023). However, not all available (recent and past) prices are equally informative. If markets are efficient, stock prices should rapidly incorporate all value-relevant signals and thus quickly become stale information. This distinctive feature is different from the environment studied in our baseline experiments, in which all information is equally important for the formation of beliefs. Our results so far show that individuals who observe information in narrow brackets overweight recent information, leading to less accurate beliefs compared to individuals who observe information in broad brackets. However, if more recent information is also more informative, observing information in narrow brackets may result in better calibrated beliefs. We test this conjecture in a third experiment (Experiment 3; $N = 998$).

The third experiment builds directly on our baseline design. To incorporate the notion that more recent information is more important, we changed the underlying data-generating process from which stock price movements are generated. Specifically, the probability of positive and negative price changes ($+/-10$) now depends on the underlying state of the asset. At first, the asset can be in a good state or bad state with equal probability. If the asset is in the good state, the probability of a positive return is 70% (and negative return 30%). If the asset is in the bad state, the probability of a positive return is 30% (and negative return 70%). The state of the asset remains fixed for 10 periods (out of 50). After every 10th period the state of the asset changes with 25% probability and remains the same with 75% probability. As such, price changes are governed by a Markov chain. A direct consequence of this Markov chain is that a Bayesian agent would overweight more recent signals as they are more diagnostic of the current state compared to older signals. The data-generating process is known to the subjects, and their understanding of it is ensured by comprehension checks. In addition to mimicking a price process representing financial markets, we conduct the experiment on a sample of more sophisticated investors who report to regularly participate in the stock market.

We start by investigating subjects' estimation error. Table 7 displays estimates of Equation 8 for the whole sample (Columns (1) and (2)), as well as for positive and negative price paths separately (Columns (3) and (4), respectively). The coefficient of $Narrow$ is highly statistically significant and of similar magnitude across all specifications, confirming that information partitioning also affects beliefs in a setting with a different data-generating process and in a sample of more financially sophisticated investors. Note that the coefficient is negative, indicating that subjects in the narrow treatment form beliefs that are closer to the Bayesian benchmark. Although this seems opposite to our previous findings, it is behaviorally consistent with a data-generating process in which more recent information is more informative about the underlying state. This conjecture rests on the assumption that

Table 7: Finance Application: Estimation Error

	Overall	Overall	Negative	Positive
bayes	-0.01	-0.01	0.18***	-0.18***
	(0.01)	(0.01)	(0.02)	(0.02)
narrow	-3.80***	-3.69***	-4.23***	-3.07***
	(0.91)	(0.91)	(1.17)	(1.07)
Controls	No	Yes	Yes	Yes
N	3,024	3,000	1,704	1,296
R^2	0.01	0.01	0.12	0.16

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

individuals in the narrow treatment put more weight on more recent information in their belief formation than those in the broad treatment, as documented in our main experiment. To ensure that this is still the case, we estimate Equation 9. Coefficient estimates are displayed in Columns (1) and (2) of Table 8. As before, we find that individuals who receive information in narrow brackets put more weight on more recent information than those who receive information in broad brackets. This finding is important as it shows that the observed behavior across experiments is identical. However, the underlying data-generating process ultimately decides whether the behavior leads to better or worse calibrated beliefs.

Table 8: Applications: Beliefs

	Finance		Consumer Choice	
	(1)	(2)	(3)	(4)
narrow	-2.36***	omitted	-0.32**	-0.30**
	(0.90)		(0.13)	(0.13)
all	0.08***	0.09***	0.94***	0.96***
	(0.01)	(0.01)	(0.11)	(0.11)
all × *narrow*	-0.00	0.00	-0.31*	-0.32*
	(0.01)	(0.01)	(0.17)	(0.17)
last	0.12***	0.11***	0.05	0.06
	(0.02)	(0.02)	(0.11)	(0.11)
last × *narrow*	0.07***	0.07***	0.51***	0.49***
	(0.02)	(0.02)	(0.17)	(0.17)
FE	No	Yes	No	No
Controls	No	No	No	Yes
N	3,024	3,024	996	989
R^2	0.54	0.54	0.13	0.13

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables. In column (1) and (2), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50) in the finance application. In column (3) and (4), All_i ($Last_i$) refers to the quality of all 15 (the last 3) ratings in the consumer choice application. In column (3) and (4), standard errors are clustered at the individual level. In column (3) and (4) standard errors are robustly estimated instead of clustered as there is only one observation per individual. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

5.2 Consumer Choice

In many online market places, consumers can learn about the quality of a good or service by reading reviews from other customers. Similarly to the information environment studied in our baseline setting, online market places typically place more equal weight on all available reviews as long as the product remains the same and is not replaced by an updated version. In contrast to the settings studied so far, these reviews are often more qualitative in nature, as customers write about their experiences and opinions. To investigate whether the partitioning of (qualitative) information into smaller or larger brackets affects consumer judgments, we conduct a fourth experiment (Experiment 4; $N = 996$).

In the experiment, subjects learn about the quality of a fictional smartphone. We chose smartphones as they are generic products with a stable quality in between new releases. To assess the quality, subjects observe a total of 15 product ratings. Each rating consists of an overall score (displayed as a 1 to 5 star rating), a short summary statement of the rating, as well as one good and one bad aspect about the phone[5]. After observing the ratings, subjects assess the quality of the phone on a scale from 1 (very bad) to 7 (very good) in 0.1 increments. The question wording was inspired by prior research on product ratings (e.g., Floyd et al., 2014; Ziegele and Weber, 2015). To establish a reasonable benchmark for quality, we follow Bhatt et al. (2015) and classify products for which the majority of the ratings display 4 and 5 stars as 'good' products and product for which the majority of the ratings display 1 and 2 stars as 'bad' products. We drew multiple sets of ratings such that the cumulative signals imply a good product in some sets and a bad product in other sets. As in our baseline experiment, we exogenously vary the frequency at which ratings are observed. In the narrow information treatment, we elicit subjects' quality assessment after every third rating and as such 5 times in total. Although subjects observe ratings in batches of 3, all previous ratings are displayed jointly with the new batch of ratings to avoid memory concerns and make the comparison as clean as possible. In the broad information treatment, we elicit subjects' quality assessment only once after all ratings have been observed.

Even in this rather simplistic setting with qualitative information signals, we find that partitioning information in smaller or larger brackets causally affects judgment. Specifically, we find that observing reviews in larger brackets (broad treatment) leads to more optimistic product ratings for good products (4.30 vs. 3.99, for broad and narrow, respectively; $p < 0.01$). For bad products, we observe a similar pattern, although less pronounced and not statistically significant (3.35 vs. 3.24, for broad and narrow respectively; $p > 0.1$), likely because consumers have much more differentiated opinions for goods with positive rather than negative evaluations in online commerce settings (Bhatt et al., 2015).

Since it is difficult to judge whether subjective ratings in the narrow or broad treatment better reflect subjects' true opinion in absence of a clear benchmark, we instead focus on how information is weighted in their final assessment. This allows us to draw inference whether

[5] All product ratings displayed in the study are AI generated without reference to a brand. Each rating has been manually evaluated to ensure its appropriateness and whether the wording is comprehensible. Screenshots of the display format are contained in Figures B11 and B12 in Appendix C.

the behavior is internally consistent with the behavior documented in our previous settings. To do so, we again compare how information early and late in the sequence affects final judgments across the broad and narrow treatment. Coefficient estimates of Equation 9 are displayed in Columns (3) and (4) of Table 8. The results confirm our previous conjecture. We observe that individuals in the narrow treatment put more weight on recently observed information, while individuals in the broad treatment put more weight on the aggregate information and less weight on recent information. Overall, this shows that our results are highly consistent across information type (qualitative vs. quantitative), setting (financial markets vs. online market places), and data-generating processes (equal-weighted information signals vs. Markov chain).

6 Alternative Explanations

6.1 Number of Trials

Subjects in narrow information treatment provide estimates more frequently and thus spend more time and effort on each stock than subjects in the broad information treatment. To avoid cognitive fatigue and enable a fair comparison between treatments, we confront subjects in the narrow information treatment with only four instead of eight trials. While our experimental design does not provide feedback after each trial, subjects might still become more familiar with the setting over the course of these trials. We therefore check whether the different number of trials between treatments affects our results. We distinguish between the first and the second half of trials per treatment. For subjects in the narrow (broad) information treatment, estimates of the first 2 (4) trials are in the first half, and estimates of the last 2 (4) trials are in the second half. Our findings remain. Even in the second half of our experiment, subjects in the narrow information treatment exhibit greater estimation errors and put more weight on recent rather than more distant observations relative to subjects in the broad information treatment (See Table A5 and A6 in Appendix B). The fact that subjects in the broad information treatment face more trials than subjects in the narrow information treatment cannot explain the information partitioning effect.

6.2 Attentiveness

Another potential concern is that some subjects are overburdened with the experiment and as a result rush through it without being attentive and making an effort. Since subjects in the narrow treatment have to provide more estimates per trial, they might become careless more easily. First, as preregistered, subjects who always provide the same estimate or – similar to the exclusion criteria of Enke and Graeber (2023) – provide estimates which deviate more than 30 percentage points from the Bayesian posterior[6] are excluded. Second, note that the analysis in the previous subsection confirms our results for the first half of trials, i.e., when attentiveness in both treatments is still high. Third, we investigate participants' total working time as a proxy for effort. If carelessness is at play, we should observe that those participants who completed the experiment the quickest are driving our results. We follow Enke and Graeber (2023) and define subjects who are in the bottom quintile of the total working time distribution as speeders. Table A7 and A8 in Appendix B report results of our main analysis excluding these speeders. If anything, results for attentive subjects are even stronger than for the entire sample. The information partitioning effect is not driven by inattentiveness.

6.3 Statistical Skill

The question remains whether our findings are transferable to more experienced and sophisticated subjects. Note that subjects in our experiments are required to answer three comprehension questions correctly before they can proceed to the actual task to ensure their understanding of the underlying setting (See Appendix C). In addition, subjects who substantially deviate from the objective benchmark as described above are excluded from our analysis. Our sample therefore comprises only of subjects who exhibit a sufficient understanding of the task. Within this sample, we further distinguish between subjects with low respectively high self-reported statistical skill[7]. While higher statistical skill is associated with lower estimation errors in general, the effect of information partitioning on estimation

[6] Since the Bayesian posterior in our design is bound between 20% and 80%, a deviation of more than 30 percentage points signals a significant misunderstanding of the task.

[7] Subjects who reported above (below or equal to) median statistical skill belong to the high (low) skill subsample.

errors is even stronger among high-skilled subjects (Table A9). Observing information at higher frequency leads also subjects with high skill to overweight recent information and underweight more distant information relative to observing information at lower frequency (Table A10). The information partitioning effect thus applies to both naive and sophisticated subjects.

6.4 Intermediate Updates

Lastly, we investigate the role of intermediate belief updating in the narrow treatment. Specifically, subjects in our narrow information treatments not only observe the information at a higher frequency, but also provide an intermediate estimate after each information bracket. In any standard model of belief updating, the influence of partitioning information at different frequencies and the updating of beliefs cannot be separated, as individuals are usually assumed to update whenever new information arrives. Our experiments were designed to reflect this property and to ensure that each subject briefly reviews the provided information. Still, we can experimentally test the influence of this intermediate updating.

In our financial markets study, we ran a third treatment in which subjects observe information in narrow brackets (i.e., the price-line chart slowly builds over time) but only provide one final estimate. We call this the *mixed* treatment. Results for the estimation error are displayed in Figure A1 in Appendix B. As can be inferred, the average estimation error in the mixed treatment is between the errors in the narrow and broad treatment. This is not unexpected. Since we cannot control whether subjects pay attention to the individual information brackets, the mixed treatment likely contains both subjects who do not pay close attention to intermediate signals and only focus on the final graph (akin to the broad treatment) and subjects who do pay attention and try to adjust their beliefs after each information bracket (akin to the narrow treatment).

7 Conclusion

In this paper, we experimentally study the influence of information partitioning on learning and beliefs. We show that partitioning information into narrower or broader brackets influences how individuals incorporate such information into their expectations. Observing information in narrower brackets causes individuals to overweight more recent information and to underweight distant information. Similar behavior cannot be observed if information is partitioned into broader brackets, where individuals appear to put equal weight on recent and distant information. Depending on the underlying data-generating process, the overweighting of recent information leads to less or more accurate judgements when information is partitioned in narrower brackets. In exploring the mechanism, we demonstrate that partitioning information into narrower brackets channels attention towards isolated information signals rather than the joint set of information. This heightened attention to small pieces of information not only leads to overextrapolation from recent signals, but also to significantly worse recall of the encountered information.

Our results imply that breaking information into smaller or larger partitions can be a powerful tool to alter individuals' expectations with applications in diverse fields. For instance, firms or information providers such as financial advisors often choose whether to disclose information regarding company performance or product ratings in narrower or broader brackets. Such choices could either willingly or unwillingly manipulate their clients' judgements. On a broader scale, one may argue that narrow bracketing enables many well-documented errors in probabilistic reasoning. For instance, individuals' belief in the law of small numbers – i.e., the belief that small random samples are highly representative of their underlying population (Tversky and Kahneman, 1971) – would have a smaller impact on judgements if information is presented in broad brackets (and thus in larger samples). Similarly, base-rate neglect – the fact that people on average under-use prior information (Kahneman and Tversky, 1973) – causes individuals to "jump to conclusions" when presented with small information samples but leads to persistent uncertainty when presented with larger samples (Benjamin, 2019). As such, the implications of base-rate neglect for belief updating also likely depend on whether information is framed in narrow or broad brackets.

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A Proofs and Derivations

A.1 Proof of Proposition 1

Proposition 1: For $\lambda = 1$ information partitioning information into smaller or larger brackets does not influence posterior beliefs ($\pi_t^{j,\text{narrow}} = \pi_t^{j,\text{broad}}$).

Proof: We first show that for $\lambda = 1$, $\mu_t^{j,\text{narrow}} = \mu_t^{j,\text{broad}} = \mu_t^{j,\text{Bayes}}$.

First, notice that for $\lambda = 1$, we obtain $\pi_{t-1}^j = \mu_{t-1}^j$ for any t. We first show that $\mu_t^{j,\text{narrow}} = \mu_t^{j,\text{Bayes}}$. Afterwards, we show that $\mu_t^{j,\text{broad}} = \mu_t^{j,\text{Bayes}}$, from which $\mu_t^{j,\text{narrow}} = \mu_t^{j,\text{broad}}$ follows.

Narrow Information Processing:

We start by rewriting the model in the posterior-odds form:

$$\frac{\mu_t^{G,\text{narrow}}}{\mu_t^{B,\text{narrow}}} = \frac{P(s_t \mid \theta_G)}{P(s_t \mid \theta_B)} \cdot \frac{P(S_{t-1} \mid \theta_G)}{P(S_{t-1} \mid \theta_B)}, \tag{10}$$

where $P(s_t \mid \theta_j)$ is the probability of observing signal s_t conditional on the type $j \in \{G, B\}$, and $P(S_{t-1} \mid \theta_G)$ is the probability of observing the full signal history S_{t-1} until period $t-1$ conditional on type $j \in \{G, B\}$.

Next, notice that $P(S_{t-1} \mid \theta_j)$ can be rewritten as $P(s_{t-1} \mid \theta_j)P(S_{t-2} \mid \theta_j)$ as the signal process is i.i.d. By continuously substituting, Equation (10) can be rewritten as:

$$\frac{\mu_t^{G,\text{narrow}}}{\mu_t^{B,\text{narrow}}} = \frac{P(S_t \mid \theta_G)}{P(S_t \mid \theta_B)} \cdot \frac{\pi_0^G}{\pi_0^B}, \tag{11}$$

where π_0^j represents the agent's prior belief about the distribution of good and bad types. This corresponds to the standard Bayesian updating process.

Broad Information Processing:

We again rewrite the model in the posterior-odds form:

$$\frac{\mu_t^{G,\text{broad}}}{\mu_t^{B,\text{broad}}} = \frac{P(s_{t:n} \mid \theta_G)}{P(s_{t:n} \mid \theta_B)} \cdot \frac{P(S_{t-n} \mid \theta_G)}{P(S_{t-n} \mid \theta_B)}, \tag{12}$$

where $P(s_{t:n} \mid \theta_j)$ is the probability of observing signals from a batch of size n in period t conditional on type $j \in \{G, B\}$, and $P(S_{t-n} \mid \theta_G)$ is the probability of observing the full signal history S_{t-n} until period $t-n$ conditional on type $j \in \{G, B\}$.

Notice that $P(s_{t:n} \mid \theta_j)$ can be rewritten as $\prod_{i=0}^{n-1} P(s_{t-i} \mid \theta_j)$ as the signal process is i.i.d. Additionally, $P(S_{t-n} \mid \theta_j)$ can be rewritten as $P(s_{t-n} \mid \theta_j)P(S_{t-n-1} \mid \theta_j)$. By continuously substituting, Equation (12) can be rewritten as:

$$\frac{\mu_t^{G,\text{broad}}}{\mu_t^{B,\text{broad}}} = \frac{P(S_t \mid \theta_G)}{P(S_t \mid \theta_B)} \cdot \frac{\pi_0^G}{\pi_0^B}, \tag{13}$$

which is the same as $\frac{\mu_t^{G,\text{narrow}}}{\mu_t^{B,\text{narrow}}}$.

Since for $\lambda = 1$, we obtain $\pi_t^j = \mu_t^j$, it follows that $\pi_t^{j,\text{narrow}} = \pi_t^{j,\text{broad}}$.

A.2 Proof of Proposition 2

Proposition 2: For $\lambda \neq 1$ information partitioning information into smaller or larger brackets generally results in different posterior beliefs ($\pi_t^{(j,\text{narrow})} \neq \pi_t^{(j,\text{broad})}$).

Proof: We first show that for narrow information processing the order of signals matters, whereas for broad information processing it does not. We then show that the two processes lead to generally different posterior beliefs. Note that for $t = 1$ the updating processes are identical as it has to follow that $n = 1$, too. We thus show that they are different for $t > 1$.

Order of signals Let σ be a permutation of the set $\Sigma = \{1, 2, \ldots, t\}$, and define the permuted signal sequence as $S'_t = (s_{\sigma(1)}, \ldots, s_{\sigma(t)})$ with $S'_t \neq S_t$.

Narrow Information Processing:

When processing one signal at a time ($n = 1$), by iterating:

$$\pi_k^{(G,\text{narrow})}(S_k) = (1-\lambda)\pi_{k-1}^{(G,\text{narrow})} + \lambda\mu_k^{(G,\text{narrow})} \quad \text{for } k = 1, \ldots, t \tag{14}$$

one shows by recursion that

$$\pi_t^{(G,\text{narrow})}(S_t) = (1-\lambda)^t \pi_0^G + \lambda \sum_{i=1}^{t} (1-\lambda)^{t-i} \mu_i^{(G,\text{narrow})} \tag{15}$$

This is exactly the same algebraic expansion used in the proof of Proposition 1 for $\lambda = 1$, but now with an extra $(1 - \lambda)$ damping at each iteration due to $\lambda \neq 1$.

Consider the permuted belief as:

$$\pi_t^{(G,\text{narrow})}(S'_t) = (1-\lambda)^t \pi_0^G + \lambda \sum_{i=1}^{t} (1-\lambda)^{t-i} \mu_{\sigma(i)}^{(G,\text{narrow})} \tag{16}$$

Then, for any $\lambda \neq 1$, there exist signal sequences S_t and S'_t, which are permutations of one another (i.e., have the same number of g and b signals), such that

$$\pi_t^{(G,\text{narrow})}(S_t) \neq \pi_t^{(G,\text{narrow})}(S'_t) \tag{17}$$

That is, the narrow belief update is not invariant to the order of signals. To show this, we proceed by constructing a simple counterexample for $t = 2$. Consider the following two sequences of signals $S_2 = (g, b)$ and $S'_{\sigma(2)} = (b, g)$.

Case 1: $S_2 = (g, b)$

The agent's first period belief is

$$\pi_1^{(G,\text{narrow})}(g) = (1-\lambda)\pi_0^G + \lambda\mu_1^{(G,\text{narrow})}(g; \pi_0^G), \tag{18}$$

where $\mu_1^{(G,\text{narrow})}(g; \pi_0^G)$ denotes the Bayesian posterior for observing signal g conditional on the prior π_0^G. Then, the agent's second period belief is

$$\pi_2^{(G,\text{narrow})}(g, b) = (1-\lambda)\pi_1^{(G,\text{narrow})}(g) + \lambda\mu_1^{(G,\text{narrow})}(b; \pi_1^{(G,\text{narrow})}(g)), \tag{19}$$

where $\mu_1^{(G,\text{narrow})}(b; \pi_1^{(G,\text{narrow})}(g))$ denotes the Bayesian posterior for observing signal b conditional on the prior $\pi_1^{(G,\text{narrow})}(g)$.

Case 2: $S'_{\sigma(2)} = (b, g)$

The agent's first period belief is

$$\pi_1^{(G,\text{narrow})}(b) = (1-\lambda)\pi_0^G + \lambda\mu_1^{(G,\text{narrow})}(b; \pi_0^G), \tag{20}$$

where $\mu_1^{(G,\text{narrow})}(b; \pi_0^G)$ denotes the Bayesian posterior for observing signal b conditional on the prior π_0^G. The second period belief is

$$\pi_2^{(G,\text{narrow})}(b, g) = (1-\lambda)\pi_1^{(G,\text{narrow})}(b) + \lambda\mu_1^{(G,\text{narrow})}(g; \pi_1^{(G,\text{narrow})}(b)), \tag{21}$$

where $\mu_1^{(G,\text{narrow})}(g; \pi_1^{(G,\text{narrow})}(b))$ denotes the Bayesian posterior for observing signal g conditional on the prior $\pi_1^{(G,\text{narrow})}(b)$.

Comparing both second period beliefs, note that $\mu_1^{(G,\text{narrow})}(g; \pi_0^G) > \pi_0^G > \mu_1^{(G,\text{narrow})}(b; \pi_0^G)$ given that $0 < \theta_B < \theta_G < 1$, i.e., signal g increases posteriors about type G, while signal b decreases them. Given that the function is increasing in $\mu_1^{(G,\text{narrow})}$, it follows that $\pi_1^{(G,\text{narrow})}(g) > \pi_0^G > \pi_1^{(G,\text{narrow})}(b)$. But then, because the posterior depends nonlinearly on the prior for $\lambda \neq 1$, we generally obtain that

$$\mu_1^{(G,\text{narrow})}(b; \pi_1^{(G,\text{narrow})}(g)) \neq \mu_1^{(G,\text{narrow})}(g; \pi_1^{(G,\text{narrow})}(b)), \tag{22}$$

and therefore

$$\pi_2^{(G,\text{narrow})}(g,b) \neq \pi_2^{(G,\text{narrow})}(b,g). \tag{23}$$

As such, the narrow belief updating for $\lambda \neq 1$ is non-commutative. In fact, for $\lambda < 1$ recent signals influence beliefs more weakly while earlier signals anchor beliefs more heavily, while for $\lambda > 1$, the opposite is the case.

Broad Information Processing

When processing the information in batches of size $n > 1$, the updating rule is:

$$\pi_t^{(G,\text{broad})}(S_t) = (1-\lambda)\pi_{t-n}^{(G,\text{broad})} + \lambda\mu_t^{(G,\text{broad})} \tag{24}$$

First, consider the agent's belief after observing the first batch of signals ($t = n$), which simplifies the updating rule to

$$\pi_t^{(G,\text{broad})}(S_t) = (1-\lambda)\pi_0^G + \lambda\mu_t^{(G,\text{broad})} \tag{25}$$

Since $\lambda \neq 1$, the ordering of signals within a batch can only matter if and only if it affects the posterior implied by the most recent batch of signals $\mu_t^{(G,\text{broad})}$. However, because signals are i.i.d. by assumption, the ordering within a batch of signals is irrelevant:

$$P(S_t|\theta_j) = \prod_{i=1}^{t} P(s_i|\theta_j) = \prod_{i=1}^{t} P(s_{\sigma(i)}|\theta_j) = P(S_{\sigma(t)}|\theta_j) \tag{26}$$

From Equation (26) immediately follows that the posterior implied by the signal $\mu_t^{(G,\text{broad})}$ is independent of the ordering of signals. Thus, by repeated substitution one can show that

$$\pi_t^{(G,\text{broad})}(S_t) = \pi_t^{(G,\text{broad})}(S_{\sigma(t)}) \tag{27}$$

holds for any $t > n$, as long as the ordering between batches does not change. Note that when the ordering between batches changes too, results for the broad information processing converge to narrow information processing for $n \to 1$, and diverge for $n \to T$.

Determining the Difference

$$\Delta = \pi_t^{(G,\text{narrow})} - \pi_t^{(G,\text{broad})} = \lambda \left[\sum_{i=1}^{t} (1-\lambda)^{t-i} \mu_i^{(G,\text{narrow})} - \mu_t^{(G,\text{broad})} \right] + [(1-\lambda)^t - (1-\lambda)]\pi_0^G \tag{28}$$

For this difference to be zero (and the posteriors between the processes to be zero) we thus require

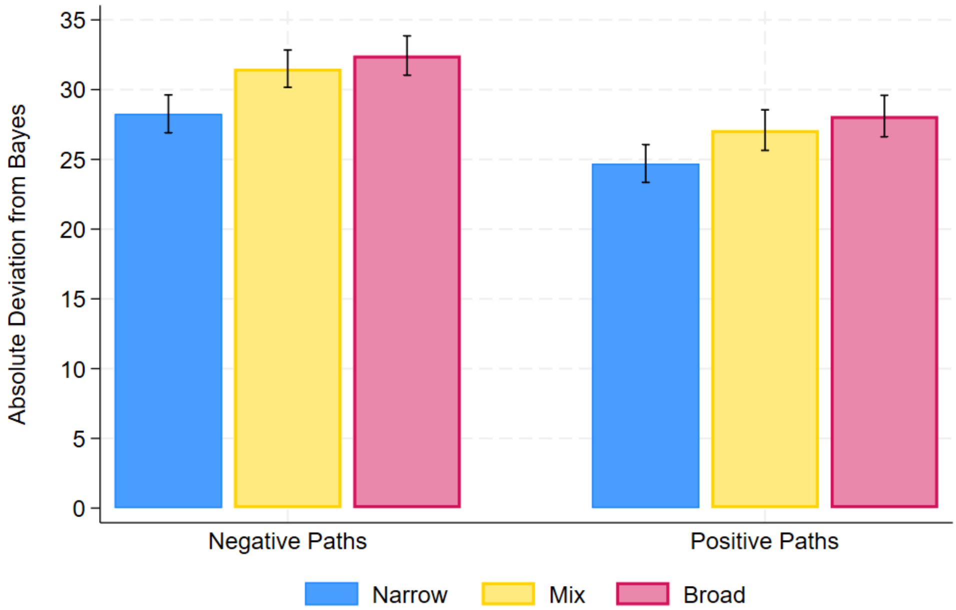
$$\lambda \left[\sum_{i=1}^{t} (1-\lambda)^{t-i} \mu_i^{(G,\text{narrow})} - \mu_t^{(G,\text{broad})} \right] = [(1-\lambda) - (1-\lambda)^t]\pi_0^G \tag{29}$$

The RHS is non-zero for $\lambda \neq 1$, but only depends on λ and the scalar π_0^G. It is independent of the signal ordering and constant for a given λ and prior π_0^G. The LHS, however, depends on the signal ordering. It thus cannot generally equal the RHS.

It follows that $\pi_t^{(j,\text{narrow})}$ is generally not equal to $\pi_t^{(j,\text{broad})}$.

B Additional Figures and Tables

Figure A1: Intermediate Updates: Estimation Error



Note: This figure plots the average estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) per treatment in the Finance Application for negative respectively positive price paths.

Table A1: Summary Statistics

Panel A: Experiment 1 (N = 713)	Full Sample	Broad	Narrow	Difference
age	41.17	41.05	41.23	0.18
	(13.53)	(13.28)	(13.64)	
female	0.48	0.46	0.49	0.03
	(0.50)	(0.50)	(0.50)	
risk aversion (1 − 7)	3.58	3.62	3.55	0.07
	(1.61)	(1.61)	(1.62)	
statistic skill (1 − 7)	4.06	3.99	4.10	0.11
	(1.38)	(1.33)	(1.40)	

Panel B: Experiment 2 (N = 352)	Full Sample
age	36.65
	(12.27)
female	0.48
	(0.50)
risk aversion (1 − 7)	3.29
	(1.57)
statistic skill (1 − 7)	4.23
	(1.36)

Note: This table displays summary statistics. Results are reported separately for Experiment 1 (Panel A) by treatment (broad vs. narrow information) and Experiment 2 (Panel B). The final column in Panel A presents t-tests for differences in means across treatments. Standard deviations are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A2: Experiment 1: Beliefs – Controls

	Δ Bayes			Δ Price		
	(1)	(2)	(3)	(4)	(5)	(6)
narrow	-0.37	omitted	-0.40	-0.37	omitted	-0.40
	(0.35)		(0.35)	(0.36)		(0.35)
all	0.98^{***}	0.99^{***}	0.98^{***}	0.08^{***}	0.08^{***}	0.08^{***}
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
all × *narrow*	-0.06^{***}	-0.07^{***}	-0.06^{***}	-0.02^{***}	-0.02^{***}	-0.02^{***}
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
last	0.13^{*}	0.13^{*}	0.14^{*}	0.02^{***}	0.01^{***}	0.02^{***}
	(0.07)	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)
last × *narrow*	0.83^{***}	0.88^{***}	0.83^{***}	0.07^{***}	0.08^{***}	$0..07^{***}$
	(0.11)	(0.12)	(0.11)	(0.01)	(0.01)	(0.01)
Controls	No	No	Yes	No	No	Yes
FE	No	Yes	No	No	Yes	No
N	3,700	3,700	3,656	3,700	3,700	3,656
R^2	0.83	0.83	0.83	0.83	0.83	0.83

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$, their interactions with the narrow information dummy and control variables as independent variables. In columns (1) to (3), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 50 (40 and 50). In columns (4) to (6), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A3: Experiment 1: Beliefs - Blocks of Information

	Δ Bayes			Δ Price		
	(1)	(2)	(3)	(4)	(5)	(6)
first40 × *narrow*	-0.07***			-0.02***		
	(0.02)			(0.00)		
last10 × *narrow*	0.81***			0.06***		
	(0.11)			(0.01)		
first30 × *narrow*		-91.08***			-0.04***	
		(12.18)			(0.01)	
last20 × *narrow*		0.79***			0.05***	
		(0.11)			(0.01)	
first20 × *narrow*			-6.58***			-0.01**
			(2.12)			(0.00)
middle20 × *narrow*			-13.27**			-0.02***
			(5.21)			(0.00)
last10 × *narrow*			0.80***			0.06***
			(0.11)			(0.01)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,700	3,700	3,700	3,700	3700	3700
R^2	0.83	0.81	0.83	0.83	0.72	0.82

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, different blocks of information, and their interaction with the narrow information dummy as independent variables. For conciseness, only the coefficients on the interactions are reported. In columns (1) to (3), the blocks of information refer to the change in Bayesian beliefs. In columns (4) to (6), the blocks of information refer to the change in price. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A4: Experiment 2: Accuracy

	Overall	Overall	Negative	Positive
bayes	0.01	0.01	0.26***	-0.08**
	(0.01)	(0.01)	(0.04)	(0..04)
attention	-1.30***	-1.08***	-1.29***	-0.84**
	(0.28)	(0.28)	(0.33)	(0.38)
Controls	No	Yes	Yes	Yes
N	3,412	3,360	1,677	1,683
R^2	0.01	0.03	0.05	0.03

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the attention dummy and control variables as independent variables. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A5: Experiment 1: Estimation Error – Number of Trials

Panel A: First Half	Overall	Overall	Negative	Positive
bayes	0.00	0.02	0.22***	-0.15**
	(0.01)	(0.01)	(0.05)	(0.06)
narrow	1.95***	1.91***	1.73***	2.00***
	(0.36)	(0.36)	(0.42)	(0.51)
Controls	No	Yes	Yes	Yes
N	1,850	1,828	931	897
R^2	0.02	0.04	0.07	0.05

Panel B: Second Half	Overall	Overall	Negative	Positive
bayes	-0.00	-0.00	0.27***	-0.11**
	(0.01)	(0.01)	(0.05)	(0.05)
narrow	1.45***	1.43***	1.31***	1.59***
	(0.34)	(0.33)	(0.40)	(0.43)
Controls	No	Yes	Yes	Yes
N	1,850	1,828	920	908
R^2	0.01	0.04	0.07	0.06

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables for the first respectively second half of trials. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A6: Experiment 1: Beliefs – Number of Trials

Panel A: First Half				
	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.32	omitted	-0.30	omitted
	(0.47)		(0.48)	
all	0.98***	1.01***	0.08***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
all × *narrow*	-0.09***	-0.12***	-0.02***	-0.02***
	(0.03)	(0.03)	(0.00)	(0.00)
last	0.17	0.18*	0.02**	0.02**
	(0.11)	(0.11)	(0.01)	(0.01)
last × *narrow*	0.94***	0.98***	0.08***	0.09***
	(0.16)	(0.20)	(0.01)	(0.02)
FE	No	Yes	No	Yes
N	1,850	1,850	1,850	1,850
R^2	0.81	0.81	0.81	0.81
Panel B: Second Half				
	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.41	omitted	-0.43	omitted
	(0.42)		(0.43)	
all	0.98***	0.99***	0.08***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
all × *narrow*	-0.05**	-0.05**	-0.01***	-0.01***
	(0.02)	(0.03)	(0.00)	(0.00)
last	0.09	0.09	0.01	0.01
	(0.09)	(0.10)	(0.01)	(0.01)
last × *narrow*	0.73***	0.67***	0.06***	0.06***
	(0.14)	(0.17)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	1,850	1,850	1,850	1,850
R^2	0.85	0.85	0.85	0.85

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables for the first respectively second half of trials. In columns (1) and (2), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 50 (40 and 50). In columns (3) and (4), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A7: Experiment 1: Estimation Error – Attentiveness

	Overall	Overall	Negative	Positive
bayes	-0.00	-0.00	0.23***	-0.08*
	(0.01)	(0.01)	(0.04)	(0.05)
narrow	1.86***	1.76***	1.66***	1.83***
	(0.34)	(0.33)	(0.39)	(0.43)
Controls	No	Yes	Yes	Yes
N	2,876	2,856	1,438	1,418
R^2	0.02	0.04	0.05	0.05

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables, excluding subjects in the bottom quintile of the total working time distribution. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A8: Experiment 1: Beliefs – Attentiveness

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.51	omitted	-0.53	omitted
	(0.39)		(0.40)	
all	0.99***	1.00***	0.08***	0.08***
	(0.02)	(0.02)	(0.00)	(0.00)
all × *narrow*	-0.07***	-0.08***	-0.02***	-0.02***
	(0.02)	(0.02)	(0.00)	(0.00)
last	0.13	0.13	0.02**	0.01**
	(0.08)	(0.08)	(0.01)	(0.01)
last × *narrow*	0.87***	0.92***	0.08***	0.08***
	(0.13)	(0.13)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	2,876	2,876	2,876	2,876
R^2	0.83	0.83	0.83	0.83

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables, excluding subjects in the bottom quintile of the total working time distribution. In columns (1) and (2), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A9: Experiment 1: Estimation Error – Statistical Skill

Panel A: Low Skill				
	Overall	Overall	Negative	Positive
bayes	0.00	0.00	0.33***	-0.16***
	(0.01)	(0.01)	(0.05)	(0.05)
narrow	1.49***	1.31***	1.00**	1.54***
	(0.35)	(0.35)	(0.40)	(0.49)
Controls	No	Yes	Yes	Yes
N	2,284	2,252	1,126	1,126
R^2	0.01	0.02	0.06	0.04
Panel B: High Skill				
	Overall	Overall	Negative	Positive
bayes	-0.01	-0.01	0.11*	-0.08
	(0.01)	(0.01)	(0.06)	(0.06)
narrow	2.33***	2.40***	2.44***	2.36***
	(0.48)	(0.48)	(0.56)	(0.43)
Controls	No	Yes	Yes	Yes
N	1,416	1,404	725	679
R^2	0.04	0.05	0.07	0.04

Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables for subjects with low respectively high self-reported statistical skill. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A10: Experiment 1: Beliefs – Statistical Skill

Panel A: Low Skill

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.09	omitted	-0.08	omitted
	(0.48)		(0.49)	
first 40	0.96***	0.99***	0.08***	0.08***
	(0.02)	(0.02)	(0.00)	(0.00)
first 40 × *narrow*	-0.07***	-0.09***	-0.02***	-0.02***
	(0.02)	(0.03)	(0.00)	(0.00)
last 10	0.22**	0.18*	0.02***	0.02***
	(0.10)	(0.10)	(0.01)	(0.01)
last 10 × *narrow*	0.87***	0.96***	0.08***	0.08***
	(0.15)	(0.16)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	2,284	2,284	2,284	2,284
R^2	0.82	0.82	0.82	0.82

Panel B: High Skill

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.94**	omitted	-0.93**	omitted
	(0.45)		(0.46)	
all	1.00***	1.00***	0.09***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
all × *narrow*	-0.06*	-0.05	-0.02***	-0.02***
	(0.03)	(0.03)	(0.00)	(0.00)
last	0.00	0.05	0.00	0.01
	(0.10)	(0.10)	(0.01)	(0.01)
last × *narrow*	0.79***	0.78***	0.07***	0.07***
	(0.16)	(0.17)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	1,416	1,416	1,416	1,416
R^2	0.85	0.85	0.85	0.85

Note: This table shows regressions with the final posterior belief as dependent variable and the narrow information dummy, All_i and $Last_i$ and their interactions with the narrow information dummy as independent variables for subjects with low respectively high self-reported statistical skill. In columns (1) and (2), All_i ($Last_i$) refers to the change in Bayesian beliefs between period 0 and 50 (40 and 50). In columns (3) and (4), All_i ($Last_i$) refers to the change in price between period 0 and 50 (40 and 50). Standard errors are clustered at the individual level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

C Experimental Instructions and Screenshots

Instructions

General Setting

In period 0 the stock price of a fictional stock amounts to \$400. The stock price increases or decreases every period over 50 periods. The size of the price change is always \$10, either up or down. The likelihood of a *price increase* is the same for these 50 periods and is randomly determined in period 0. It can be any percentage number between 20% and 80%. Since there are equally many percentage numbers above and below 50%, the average probability of a price increase is 50%.

But if, for example, 62% is drawn, the likelihood of a price increase is 62% in each period and the likelihood of a price decrease is 38% (100%-62%) in each period. As such, price increases and decreases are indicative of the drawn likelihood of a *price increase* for the fictional stock.

Task

You will observe the price changes of the fictional stock over 50 periods. From time to time you are asked to estimate the randomly determined likelihood of a *price increase* for this stock. In particular, you have to enter an integer percentage number between 20% and 80%. The entire task is repeated up to 8 times for independent fictional stocks, i.e. each stock has its own randomly determined likelihood of a price increase.

On the next page the compensation scheme is described.

Compensation

In addition to the participation fee of £1.50, you can earn a bonus payment in the estimation task.

Three of your estimates are randomly selected at the end of the study. Your compensation increases by £0.30 for each estimate which is within 5% of the correct statistical probability of a price increase (e.g. the correct probability is 50% and your estimate is between 45% and

55%).

If you feel that you understand the instructions, press “Next” to proceed to answer a few comprehension questions before the experiment starts.

Comprehension Questions

Below we report the comprehension questions that subjects had to answer correctly after reading the instructions to proceed to the estimation task. Correct responses are displayed in bold.

1. You observe a price change of $-10, how do you have to update your probability estimate of a price increase?

    - I increase the probability estimate.
    - **I decrease the probability estimate.**

2. Assume the correct statistical probability of a price increase is 70%. Which probability estimate would be in the range such that you earn a bonus payment?

    - 55%
    - **67%**
    - 77%
    - 83%

3. Is a probability estimate of 50% reasonable before having seen any price changes?

    - **Yes**
    - No
    - Can't be answered

Screenshots of the Estimation Task

Figures B1 to B4 present the screens of the estimation task as seen by subjects in the experiment (using example stock 1). One round consists of three sequential screens. First, subjects see the empty price-line chart, only indicating the starting price of 400 in period 0. Second, the price development appears on the price-line-chart. In the narrow information treatment, the price-line chart builds over time and subjects beliefs about the asset's fundamental are elicited every 10 periods. In the broad information treatment, subjects observe all price changes between period 1 and 50 at once and their beliefs are only elicited in period 50. Finally, subjects are informed that they reached the end of the estimation task for this stock and will continue with the next stock.

Figure B1: Start of the Estimation Task

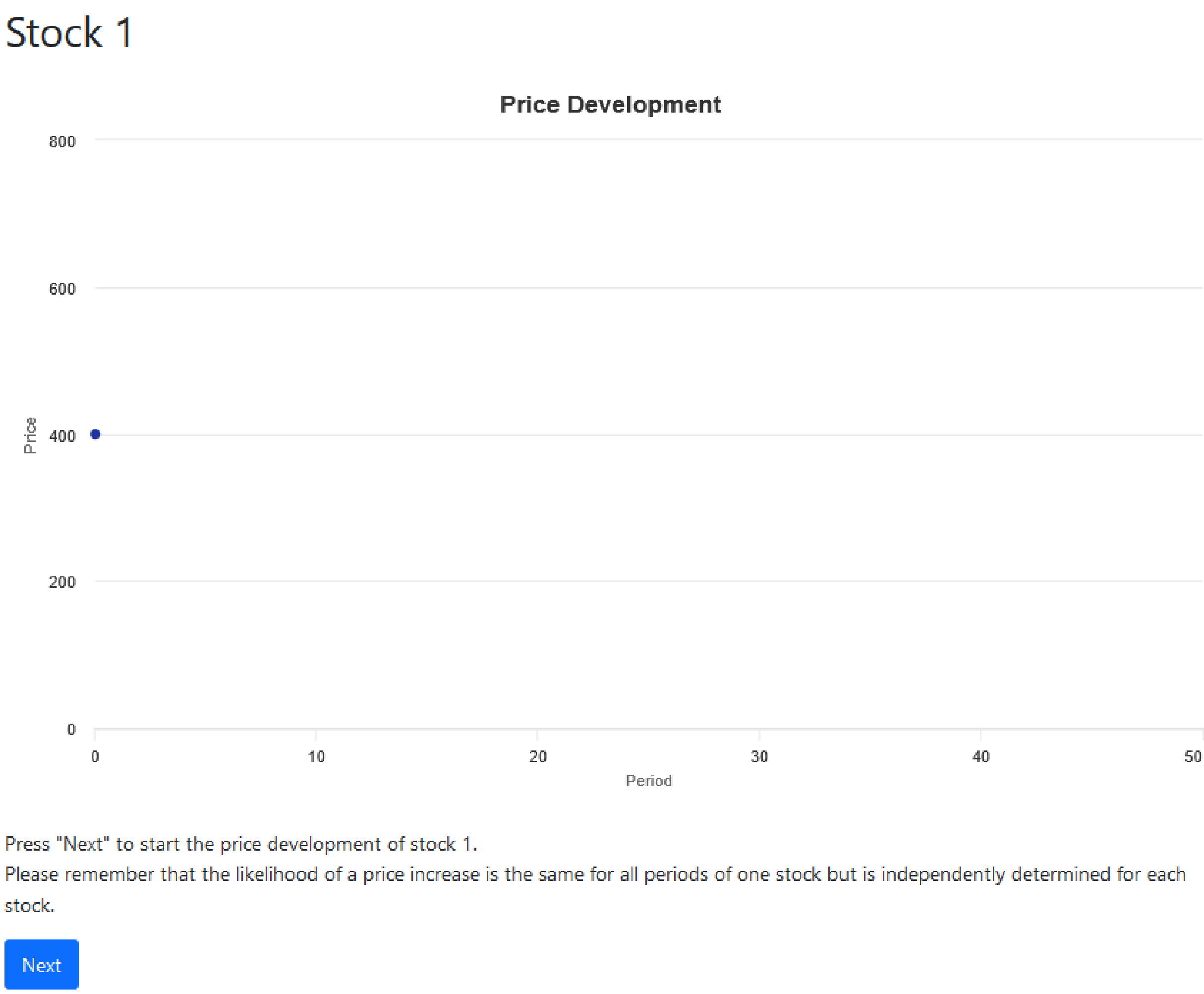


Figure B2: Belief Eliciation in Period 10

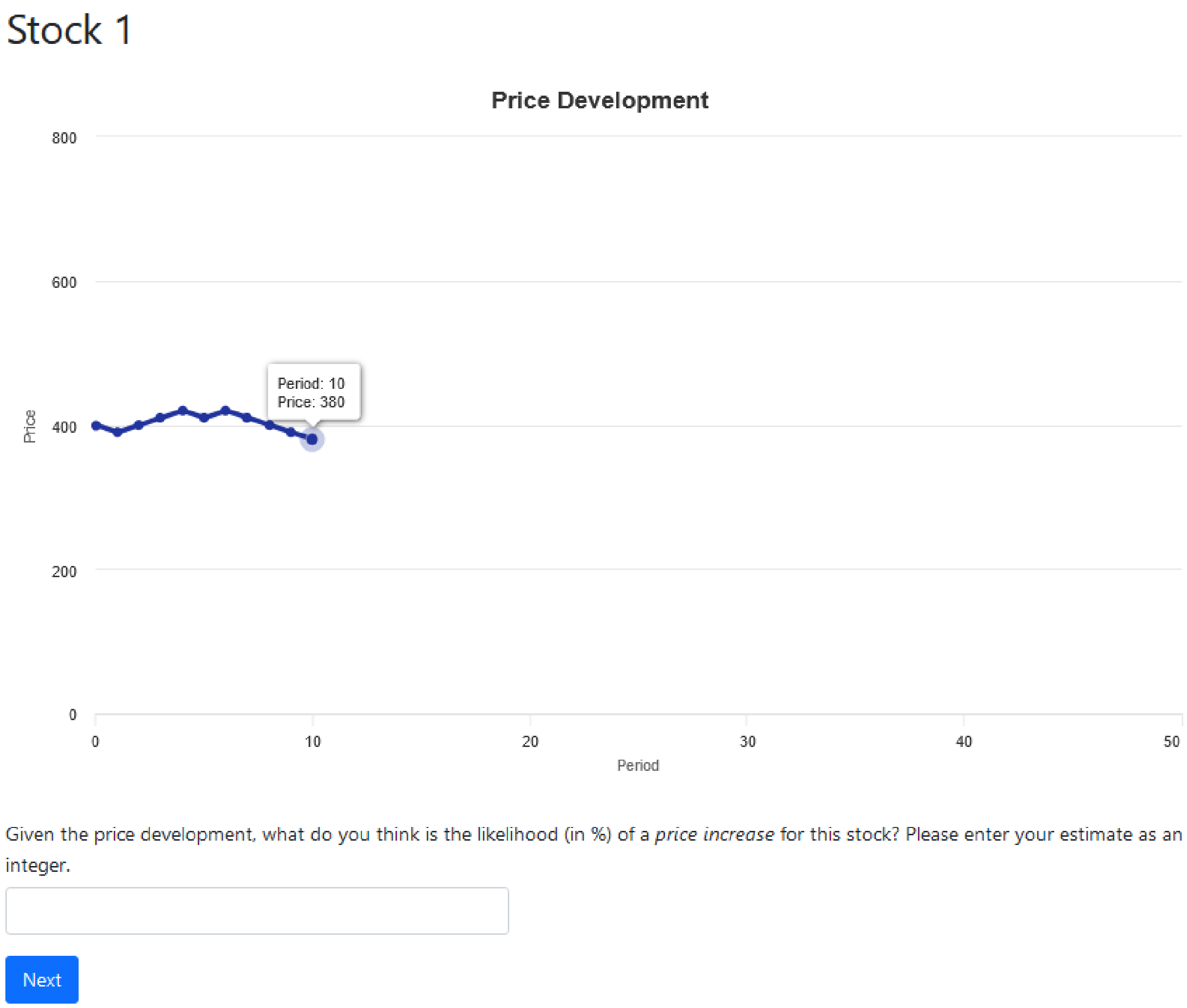


Figure B3: Belief Eliciation in Period 50

Stock 1

Given the price development, what do you think is the likelihood (in %) of a *price increase* for this stock? Please enter your estimate as an integer.

Next

Figure B4: End of the Estimation Task

Last Period for Stock 1

You have reached the last period for stock 1.
Press "Next" to observe the price development of the next stock, for which the likelihood of a *price increase* is again randomly determined in period 0.

Next

Screenshots of the Recall Task

Figures B5 to B8 present the screens of the recall task as seen by subjects in the experiment. The recall task consists of four sequential screens. First, the recall task is introduced to the subjects. Second, subjects are asked to recall the number of price increases and decreases they observed. Third, they are asked to recall the final price they observed. Finally, subjects are asked to recall the maximum number of subsequent price increases and decreases they observed.

Figure B5: Start of the Recall Task

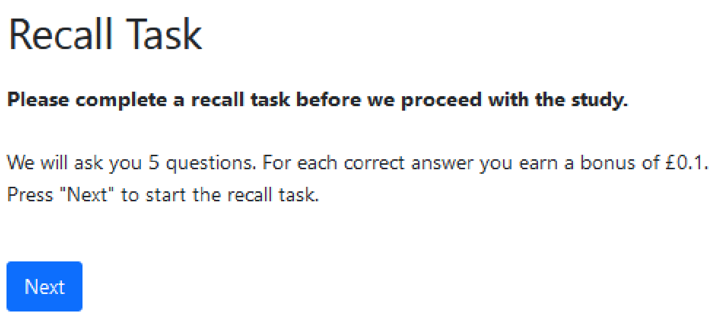


Figure B6: Recall Questions Page 1

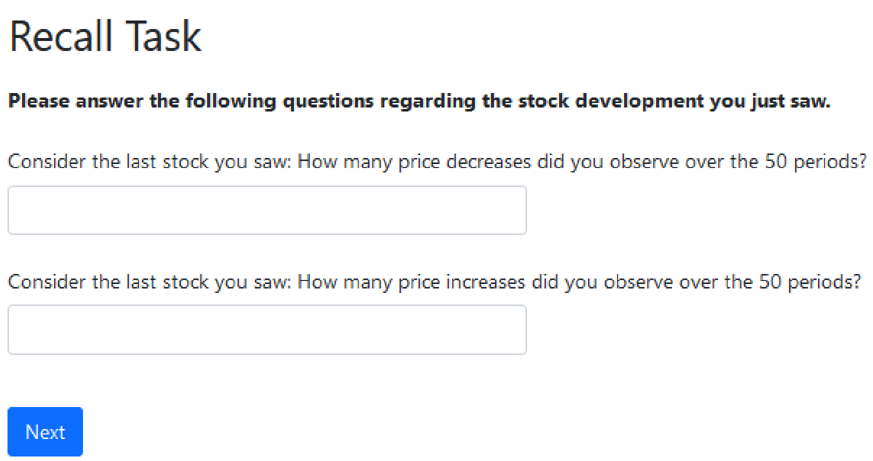


Figure B7: Recall Questions Page 2

Recall Task

Please answer the following questions regarding the stock development you just saw.

Consider the last stock you saw: What was the price of the stock in period 50?

Next

Figure B8: Recall Questions Page 3

Recall Task

Please answer the following questions regarding the stock development you just saw.

Consider the last stock you saw: If you had to guess, what is the maximum number of subsequent periods in which the the price repeatedly increased?

Consider the last stock you saw: If you had to guess, what is the maximum number of subsequent periods in which the the price repeatedly decreased?

Next

Screenshots of Attention Manipulation in Experiment 2

Figure B9 and Figure B10 present the screens of the attention manipulation as seen by subjects in the second experiment. The attention manipulation consists of two sequential screens. First, subjects start the rebuild of the price path. Second, once the rebuild is completed, subjects are asked to identify the asset's price for 5 periods.

Figure B9: Start of the Rebuild

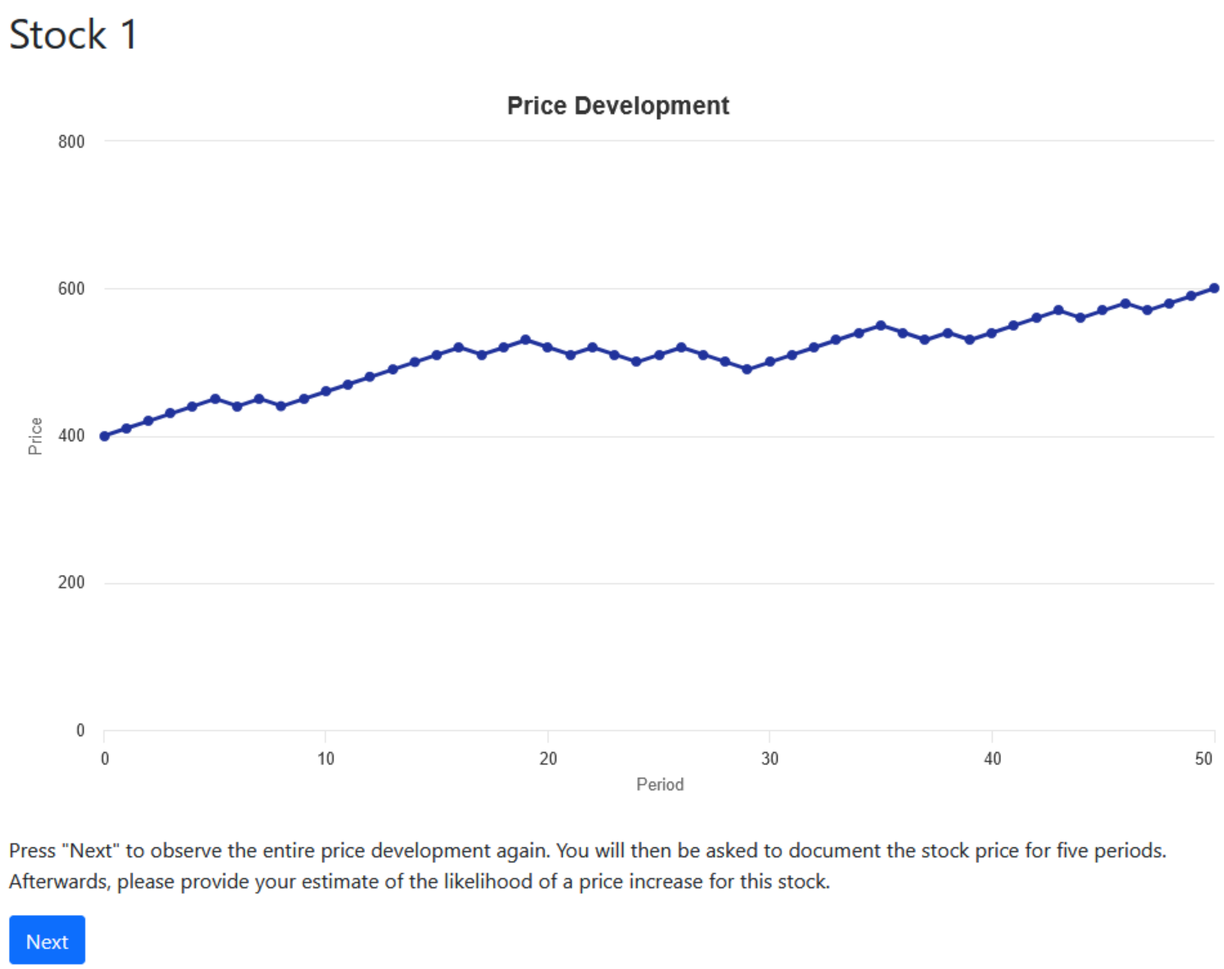
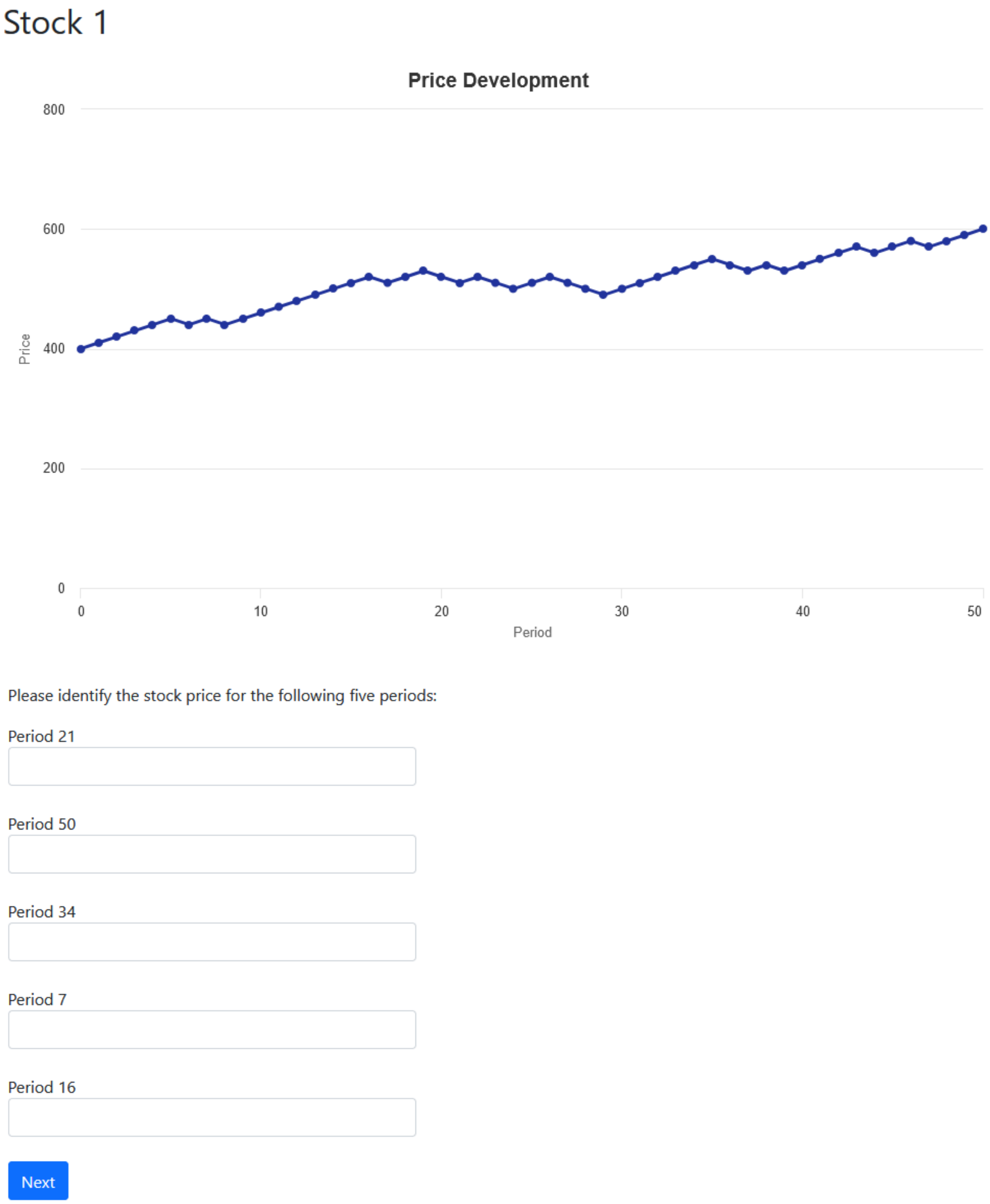


Figure B10: Price Identification



Screenshots of Product Ratings in Consumer Choice Application

Figure B11 and Figure B12 present the screens of the product ratings as seen by subjects in the consumer choice application. In the narrow information treatment, subjects observe 3 product ratings at a time with the new ratings being presented on top of the previous ratings. In the broad information treatment, subjects observe all 15 product ratings at once.

Figure B11: Product Ratings - Narrow Treatment

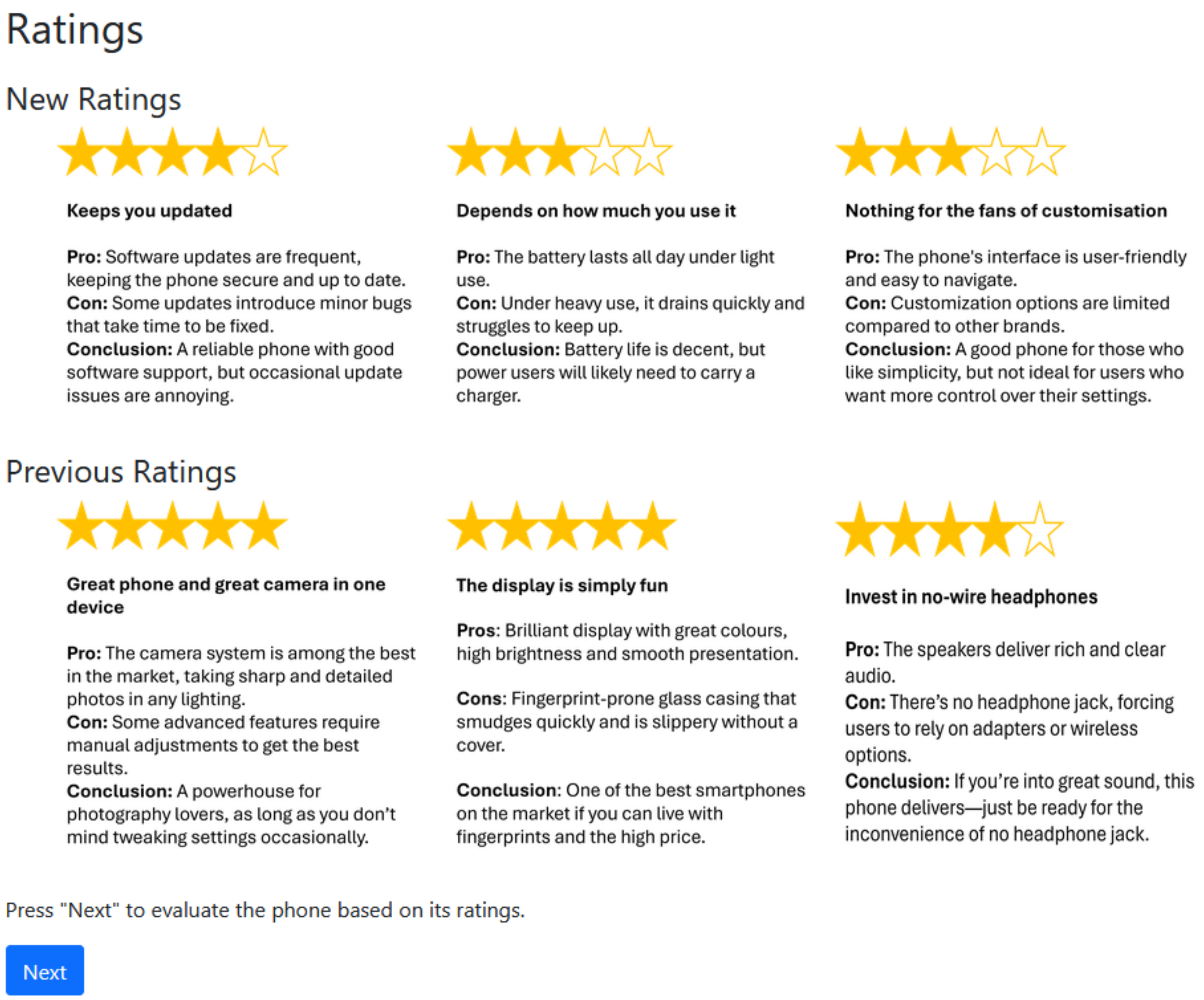
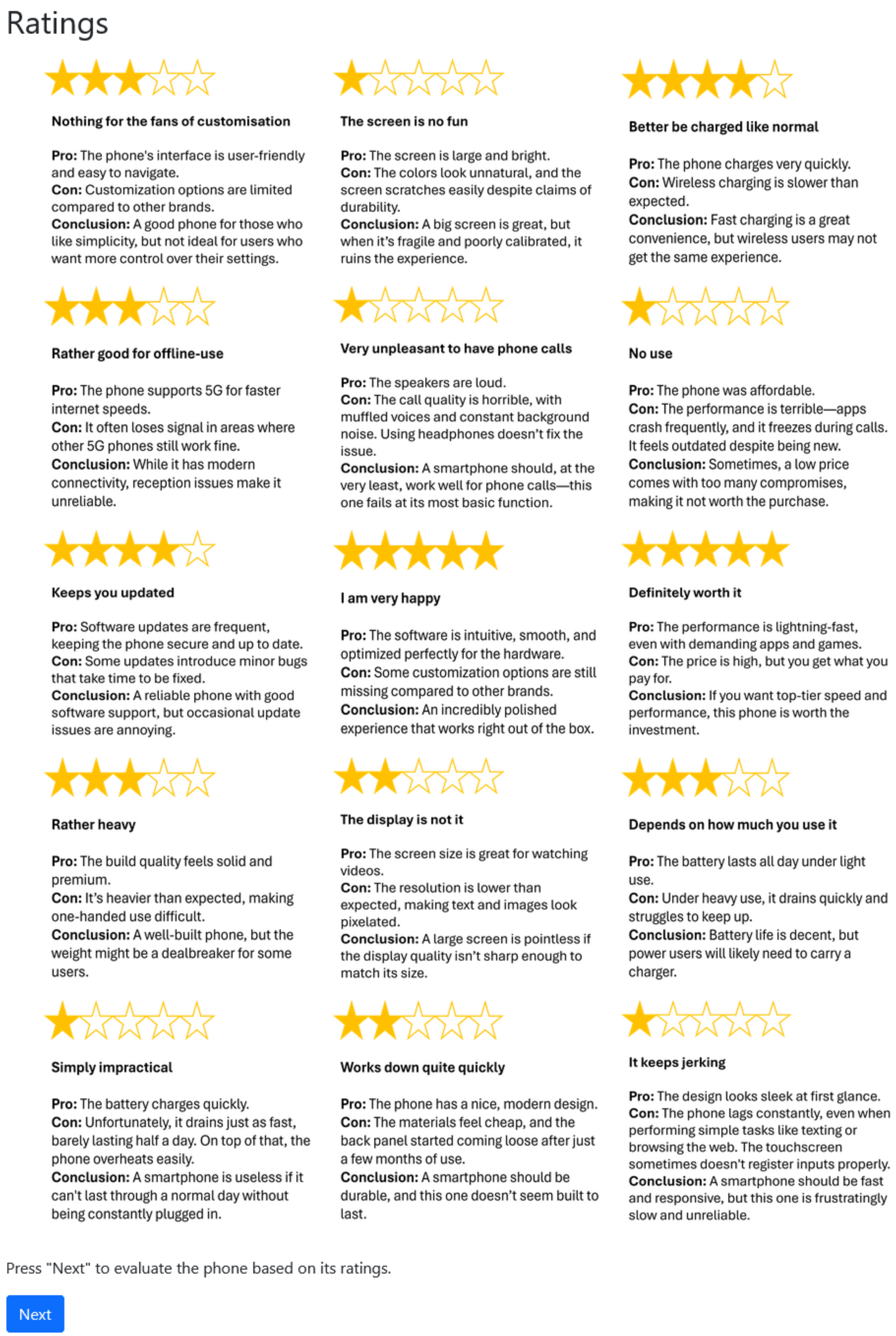


Figure B12: Product Ratings - Broad Treatment



Ratings

Nothing for the fans of customisation

Pro: The phone's interface is user-friendly and easy to navigate.
Con: Customization options are limited compared to other brands.
Conclusion: A good phone for those who like simplicity, but not ideal for users who want more control over their settings.

The screen is no fun

Pro: The screen is large and bright.
Con: The colors look unnatural, and the screen scratches easily despite claims of durability.
Conclusion: A big screen is great, but when it's fragile and poorly calibrated, it ruins the experience.

Better be charged like normal

Pro: The phone charges very quickly.
Con: Wireless charging is slower than expected.
Conclusion: Fast charging is a great convenience, but wireless users may not get the same experience.

Rather good for offline-use

Pro: The phone supports 5G for faster internet speeds.
Con: It often loses signal in areas where other 5G phones still work fine.
Conclusion: While it has modern connectivity, reception issues make it unreliable.

Very unpleasant to have phone calls

Pro: The speakers are loud.
Con: The call quality is horrible, with muffled voices and constant background noise. Using headphones doesn't fix the issue.
Conclusion: A smartphone should, at the very least, work well for phone calls—this one fails at its most basic function.

No use

Pro: The phone was affordable.
Con: The performance is terrible—apps crash frequently, and it freezes during calls. It feels outdated despite being new.
Conclusion: Sometimes, a low price comes with too many compromises, making it not worth the purchase.

Keeps you updated

Pro: Software updates are frequent, keeping the phone secure and up to date.
Con: Some updates introduce minor bugs that take time to be fixed.
Conclusion: A reliable phone with good software support, but occasional update issues are annoying.

I am very happy

Pro: The software is intuitive, smooth, and optimized perfectly for the hardware.
Con: Some customization options are still missing compared to other brands.
Conclusion: An incredibly polished experience that works right out of the box.

Definitely worth it

Pro: The performance is lightning-fast, even with demanding apps and games.
Con: The price is high, but you get what you pay for.
Conclusion: If you want top-tier speed and performance, this phone is worth the investment.

Rather heavy

Pro: The build quality feels solid and premium.
Con: It's heavier than expected, making one-handed use difficult.
Conclusion: A well-built phone, but the weight might be a dealbreaker for some users.

The display is not it

Pro: The screen size is great for watching videos.
Con: The resolution is lower than expected, making text and images look pixelated.
Conclusion: A large screen is pointless if the display quality isn't sharp enough to match its size.

Depends on how much you use it

Pro: The battery lasts all day under light use.
Con: Under heavy use, it drains quickly and struggles to keep up.
Conclusion: Battery life is decent, but power users will likely need to carry a charger.

Simply impractical

Pro: The battery charges quickly.
Con: Unfortunately, it drains just as fast, barely lasting half a day. On top of that, the phone overheats easily.
Conclusion: A smartphone is useless if it can't last through a normal day without being constantly plugged in.

Works down quite quickly

Pro: The phone has a nice, modern design.
Con: The materials feel cheap, and the back panel started coming loose after just a few months of use.
Conclusion: A smartphone should be durable, and this one doesn't seem built to last.

It keeps jerking

Pro: The design looks sleek at first glance.
Con: The phone lags constantly, even when performing simple tasks like texting or browsing the web. The touchscreen sometimes doesn't register inputs properly.
Conclusion: A smartphone should be fast and responsive, but this one is frustratingly slow and unreliable.

Press "Next" to evaluate the phone based on its ratings.

Next