Information Partitioning, Learning, and Beliefs*

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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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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 two 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.

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

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

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 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 Experimental Design

2.1 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 two 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. 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.*

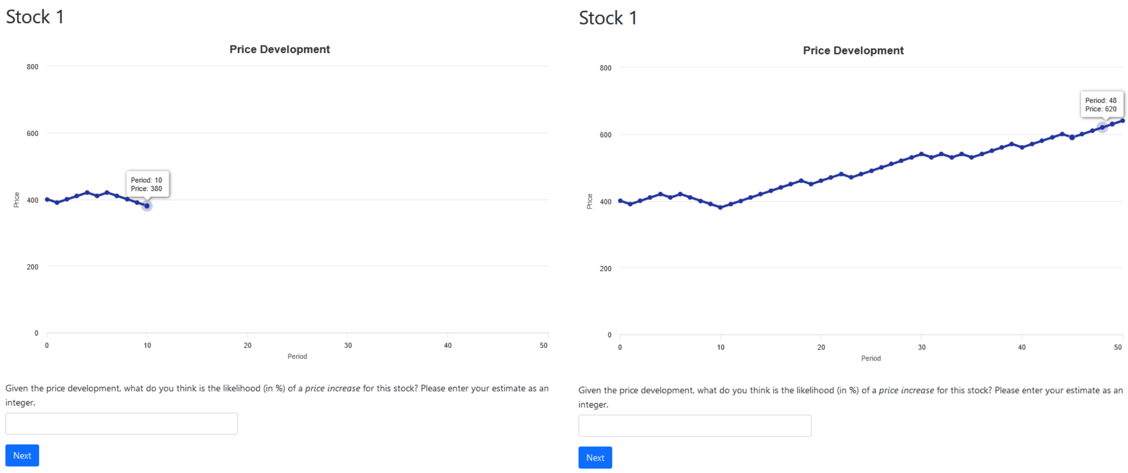
In the *narrow information* treatment, we elicit subjects' beliefs about the asset's fundamental quality every 10 periods. This treatment aims to elicit beliefs when information arrives in small amounts at higher frequency. Subjects start with an empty price-line chart at period $t = 0$ which *builds* 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).

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

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.

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 probabilities 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 probabilities greater than 50%. Finally, we mirrored each price path to obtain another 12 price paths for probabilities 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.

2.2 Recruitment Procedure

The experiment was computerized using oTree (Chen et al., 2016). We recruited in total 1065 individuals from a large crowdsourcing platform called Prolific to participate in two experiments. The design, hypothesis, and sample selection criteria are all preregistered[2].

[2] The preregistration document for the baseline experiment can be found at https://aspredicted.org/LJ1_GZ3, while the preregistration document for the attention manipulation can be found at https://aspredicted.org/DJP_5ZZ.

The study obtained ethics approval by the Institutional Review Board of the University of Mannheim. The subject pool is comprised of subjects from the UK. To overcome the imbalance between males and females in the Prolific subject pool, we collected the sample as a stratified representation based on subjects' gender. Each subject was only allowed to participate in one experiment by excluding their unique subject ID from the available subject pool after they had successfully participated in one of the experiments. Summary statistics are contained in Table A1 in Appendix A.

3 Results

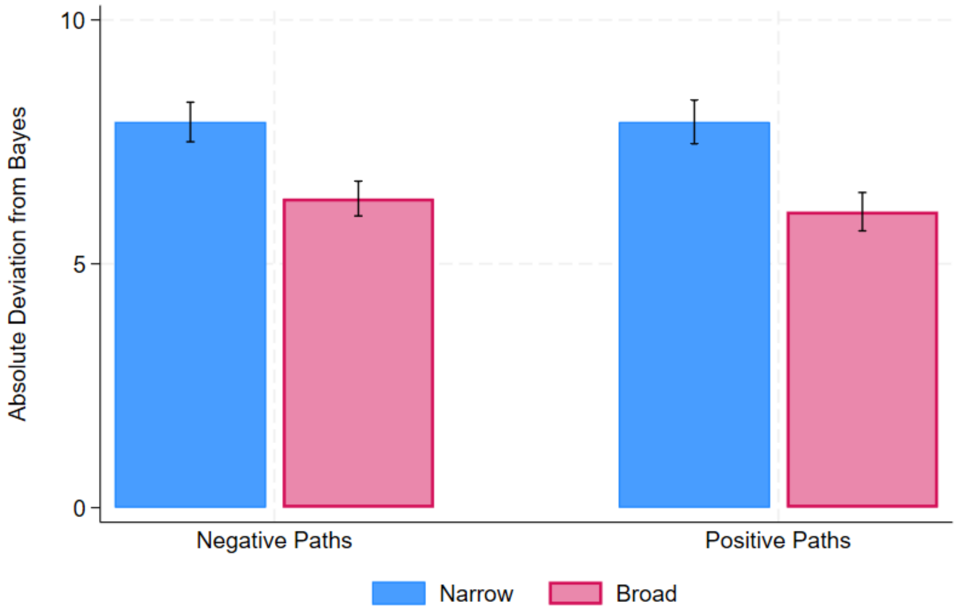
3.1 Information Partitioning and Learning

Accuracy of 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.

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.

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.

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:

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

We regress subjects' estimation error 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 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 $NarrowInfo$ 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.

Table 1: Experiment 1: Estimation Error

	Overall	Overall	Negative	Positive
bayes	-0.07	-0.09	0.25^{***}	-0.13^{***}
	(0.49)	(0.49)	(0.04)	(0.04)
narrow info	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

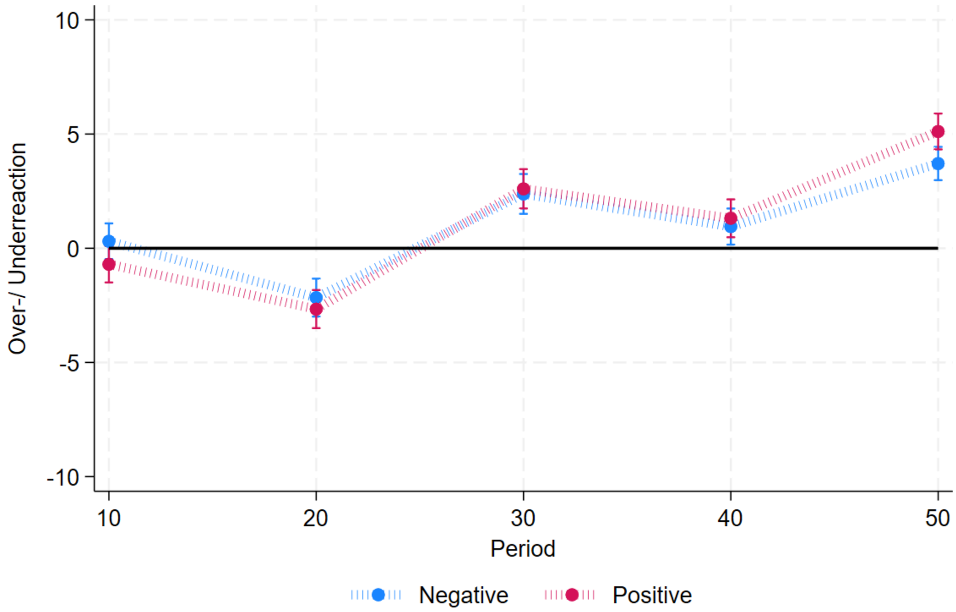
Note: This table shows regressions with the estimation error (absolute difference between reported beliefs and Bayesian beliefs in period 50) as dependent variable and the Bayesian posterior, the narrow information dummy and control variables as independent variables. Standard errors are clustered at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

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 the movement of subjects' beliefs relative to the Bayesian benchmark over the 50 periods. Figure 3 plots the average belief update relative to the Bayesian benchmark for each period. Positive values reflect overreactions (belief updates which are too extreme), and negative values reflect underreactions (belief updates which are too moderate).

On aggregate, belief updates are relatively close to the Bayesian benchmark. However, it appears that subjects' belief updating changes over time. Whereas belief updates are too moderate early on, they progressively become more extreme. From period 30 onwards, we observe pronounced overreactions in belief updating for both negative (blue line) and positive (red line) price paths, with no difference between the two. This pattern offers two insights. First, information that is observed early in the sequence is only insufficiently accounted for when updating expectations, while information that is observed more recently receives disproportionate weight. Second, the pattern is consistent with the idea of diagnostic expectations (Bordalo et al., 2018; Bordalo et al., 2019; Bordalo et al., 2022), in which subjects seem to overextrapolate from information when it is representative of the recent

Figure 3: Experiment 1: Belief Movement



Note: This figure plots the average belief update relative to the Bayesian update over the 50 periods in Experiment 1 for negative (blue) respectively positive (red) price paths. Positive values reflect an overreaction, and negative values an underreaction.

trend. While information that is observed early in the sequence is insufficient to establish a trend, information that occurs later in the sequence is on average consistent with the increasing or decreasing trend, which leads to overextrapolation.

Next, we investigate this pattern more closely. In particular, while our previous analysis only focused on the narrow treatment, we now test whether partitioning information into narrower or broader brackets affects how subjects weight recent and more distant observations when forming their beliefs. To do so, we run the following regression:

$$Estimate_i = \alpha + \beta_1 NarrowInfo_i + \beta_2 First40_i + \beta_3 First40_i * NarrowInfo_i$$
$$+\beta_4 Last10_i + \beta_5 Last10_i * NarrowInfo_i + \epsilon_i$$

We regress subjects' final posterior belief p^i in round 50 on the $NarrowInfo$ dummy, as well as on two variables, $First40_i$ and $Last10_i$, that both capture blocks of information, and their interaction with the treatment dummy. Specifically, $First40_i$ corresponds to information observed within the first 40 periods, while $Last10_i$ corresponds to information observed within the last 10 periods. In Columns (1) and (2) of Table 2, $First40_i$ ($Last10_{it}$) is defined as the change in Bayesian beliefs between period 0 and 40 (40 and 50). In Columns (3) and (4), $First40_i$ ($Last10_i$) is defined as the risky asset's change in price between period 0 and 40 (40 and 50)[3].

Table 2: Experiment 1: Beliefs

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.37	omitted	-0.37	omitted
	(0.35)		(0.36)	
first 40	0.98^{***}	0.99^{***}	0.08^{***}	0.08^{***}
	(0.01)	(0.01)	(0.00)	(0.00)
first 40 × narrow	-0.06^{***}	-0.07^{***}	-0.02^{***}	-0.02^{***}
	(0.02)	(0.02)	(0.00)	(0.00)
last 10	1.11^{***}	1.12^{***}	0.10^{***}	0.10^{***}
	(0.07)	(0.07)	(0.00)	(0.00)
last 10 × narrow	0.76^{***}	0.81^{***}	0.06^{***}	0.06^{***}
	(0.11)	(0.11)	(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, $First40_i$ and $Last10_i$ and their interactions with the narrow information dummy as independent variables. In columns (1) and (2), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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.

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, irrespective of whether the informational content is measured via Bayesian beliefs or price changes, subjects in the narrow treatment put less weight on more distant 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.

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

3.2 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 neither consistent with models of motivated beliefs (e.g., Kunda, 1990; Brunnermeier and Parker, 2005) nor 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. 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 beliefs to become overly sensitive, which leads to the observed patterns of overinference 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. A number of studies argues that 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 the fractions in the broad information treatment equal roughly 1.5 times the fractions 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 influence of memory on beliefs, by regressing subjects'

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.

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 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 influence of memory on beliefs is not affected by how information is partitioned.

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 info	1.53***	1.59***		
	(0.28)	(0.34)		
memory score × *narrow info*		0.03		
		(0.23)		
N	3,700	3,700	2,004	1,672
R^2	0.05	0.05	0.02	0.04

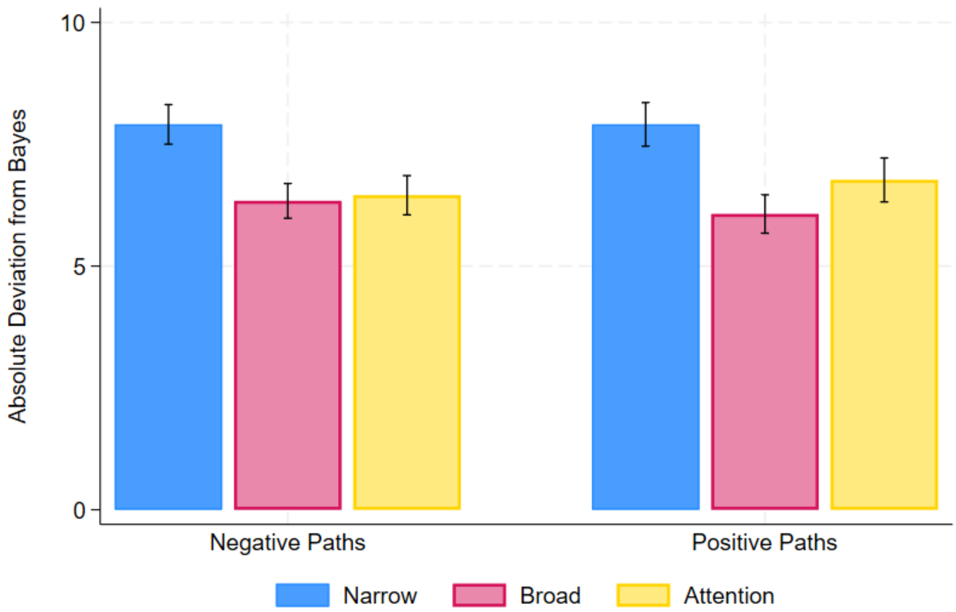
Note: This table shows regressions with the absolute deviation of the subjects' beliefs from the Bayesian posterior as dependent variable and the memory score, and control variables as independent variables. Standard errors are clustered at the individual level and reported in parentheses. ***, **, and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

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 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), 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 B.). 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 4 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 4: 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 A3 in Appendix A 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:

$$Estimate_i = \alpha + \beta_1 Attention_i + \beta_2 First40_i + \beta_3 First40_i * Attention_i$$
$$+\beta_4 Last10_i + \beta_5 Last10_i * Attention_i + \epsilon_i$$

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)	
first 40	0.91^{***}	0.92^{***}	0.07^{***}	0.07^{***}
	(0.01)	(0.01)	(0.00)	(0.00)
first 40 × *attention*	0.11^{***}	0.12^{***}	0.02^{***}	0.02^{***}
	(0.02)	(0.02)	(0.00)	(0.00)
last 10	1.88^{***}	1.93^{***}	0.15^{***}	0.16^{***}
	(0.08)	(0.07)	(0.01)	(0.01)
last 10 × *attention*	-0.59^{***}	-0.74^{***}	-0.04^{***}	-0.05^{***}
	(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, $First40_i$ and $Last10_i$ and their interactions with the narrow information dummy as independent variables. In columns (1) and (2), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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 %		
	Experiment 2	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					
	Experiment 2	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.

[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.

3.3 Alternative Explanations

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 A4 and A5 in Appendix A). 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.

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[5] 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

[5] 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.

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 A6 and A7 in Appendix A 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.

Statistical Skill

Lastly, 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 B). 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[6]. While higher statistical skill is associated with lower estimation errors in general, the effect of information partitioning on estimation errors is even stronger among high-skilled subjects (Table A8). 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 A9). The information partitioning effect thus applies to both naive and sophisticated subjects.

4 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

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

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. This different weighting of information leads to less accurate judgements and greater probability estimation errors 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 Additional Tables

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)
first 40	0.98***	0.99***	0.98***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
first 40 × *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 10	1.11***	1.12***	1.11***	0.10***	0.10***	0.10***
	(0.07)	(0.07)	(0.07)	(0.00)	(0.00)	(0.00)
last 10 × *narrow*	0.76***	0.81***	0.77***	0.06***	0.06***	0.06***
	(0.11)	(0.11)	(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, $First40_i$ and $Last10_i$, their interactions with the narrow information dummy and control variables as independent variables. In columns (1) to (3), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (4) to (6), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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 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 A4: 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 info	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 info	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 A5: 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)	
first 40	0.98***	1.01***	0.08***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
first 40 $\times$ *narrow*	-0.09***	-0.12***	-0.02***	-0.02***
	(0.03)	(0.03)	(0.00)	(0.00)
last 10	1.15***	1.20***	0.10***	0.11***
	(0.10)	(0.11)	(0.01)	(0.01)
last 10 $\times$ *narrow*	0.85***	0.86***	0.06***	0.06***
	(0.15)	(0.19)	(0.01)	(0.01)
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)	
first 40	0.98***	0.99***	0.08***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
first 40 $\times$ *narrow*	-0.05**	-0.05**	-0.01***	-0.01***
	(0.02)	(0.03)	(0.00)	(0.00)
last 10	1.07*	1.08***	0.09***	0.09***
	(0.09)	(0.10)	(0.01)	(0.01)
last 10 $\times$ *narrow*	0.68***	0.62***	0.05***	0.04***
	(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, $First40_i$ and $Last10_i$ and their interactions with the narrow information dummy as independent variables for the first respectively second half of trials. In columns (1) and (2), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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 A6: Experiment 1: Estimation Error – Attentiveness

	Overall	Overall	Negative	Positive
bayes	-0.00	-0.00	0.24***	-0.09**
	(0.01)	(0.01)	(0.04)	(0.04)
narrow info	1.84***	1.78***	1.65***	1.88**
	(0.34)	(0.32)	(0.38)	(0.42)
controls	No	Yes	Yes	Yes
N	2,968	2,944	1,478	1,466
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 A7: Experiment 1: Beliefs – Attentiveness

	Δ Bayes		Δ Price	
	(1)	(2)	(3)	(4)
narrow	-0.51	omitted	-0.53	omitted
	(0.39)		(0.39)	
first 40	0.98***	1.00***	0.08***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
first 40 × *narrow*	-0.07***	-0.08***	-0.02***	-0.02***
	(0.02)	(0.02)	(0.00)	(0.00)
last 10	1.11***	1.11***	0.10***	0.10***
	(0.08)	(0.08)	(0.01)	(0.01)
last 10 × *narrow*	0.81***	0.86***	0.05***	0.06***
	(0.12)	(0.13)	(0.01)	(0.01)
FE	No	Yes	No	Yes
N	2,968	2,8968	2,968	2,968
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, $First40_i$ and $Last10_i$ 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), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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 A8: 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 info	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 info	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 A9: 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	1.18***	1.16***	0.10***	0.10***
	(0.09)	(0.09)	(0.01)	(0.01)
last 10 × *narrow*	0.80***	0.87***	0.06***	0.06***
	(0.14)	(0.15)	(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)	
first 40	1.00***	1.00***	0.09***	0.09***
	(0.02)	(0.02)	(0.00)	(0.00)
first 40 × *narrow*	-0.06*	-0.05	-0.02***	-0.02***
	(0.03)	(0.03)	(0.00)	(0.00)
last 10	1.00***	1.05***	0.09***	0.09***
	(0.10)	(0.10)	(0.01)	(0.01)
last 10 × *narrow*	0.73***	0.74***	0.05***	0.06***
	(0.16)	(0.16)	(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, $First40_i$ and $Last10_i$ 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), $First40_i$ ($Last10_i$) refers to the change in Bayesian beliefs between period 0 and 40 (40 and 50). In columns (3) and (4), $First40_i$ ($Last10_i$) refers to the change in price between period 0 and 40 (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.

B 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

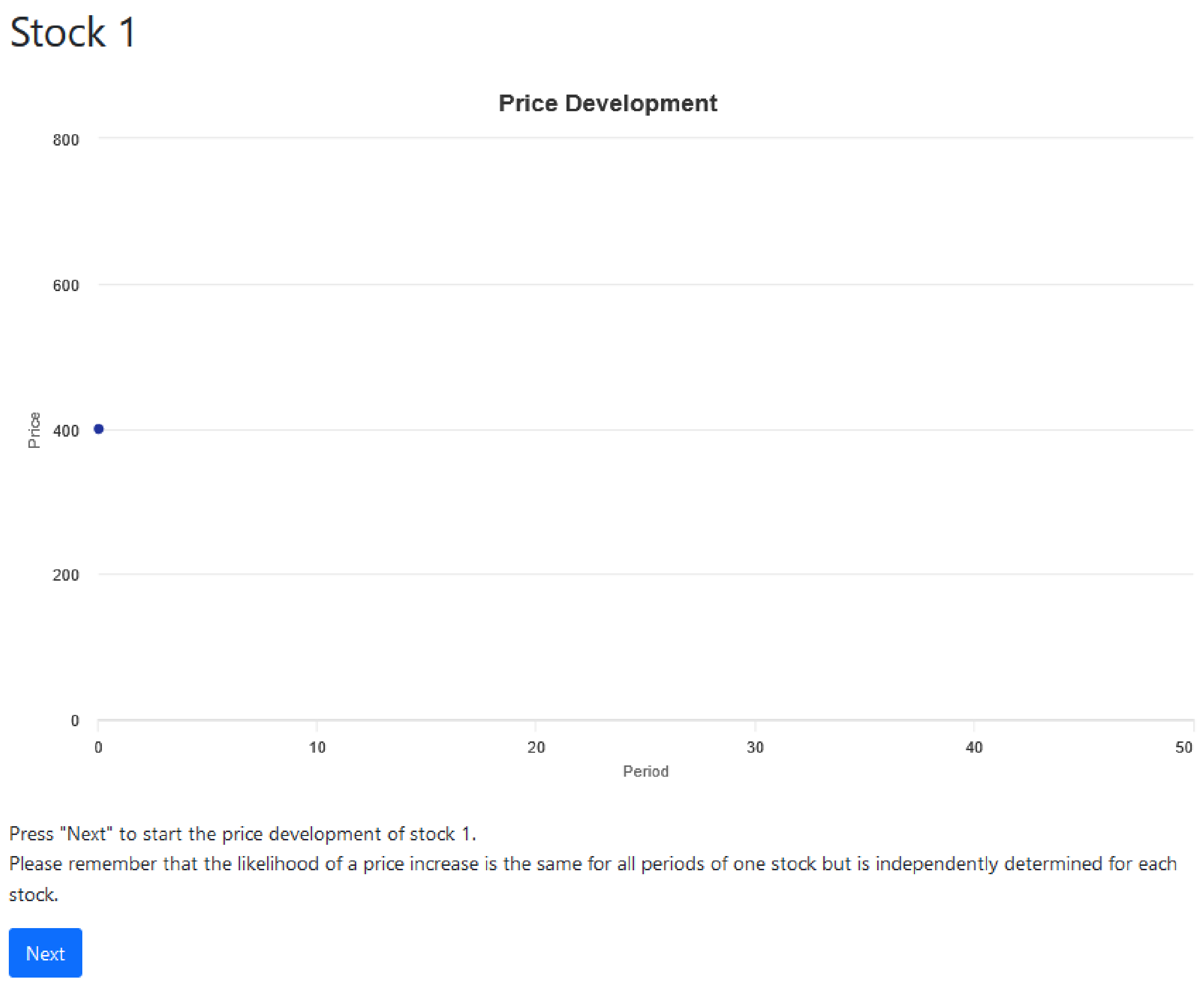
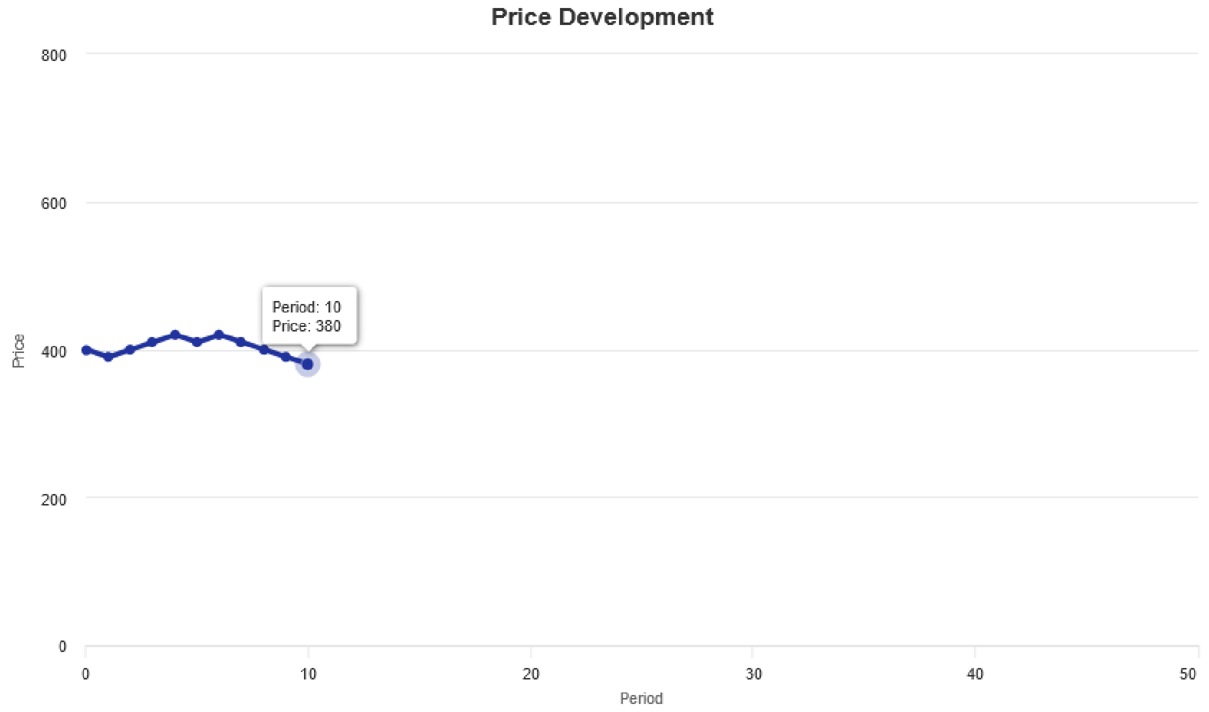


Figure B2: Belief Eliciation in Period 10

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 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

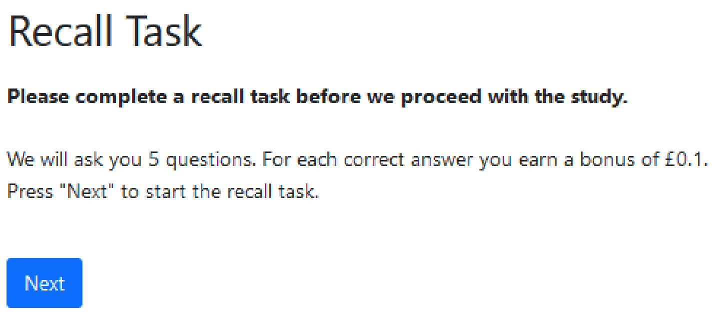


Figure B6: Recall Questions Page 1

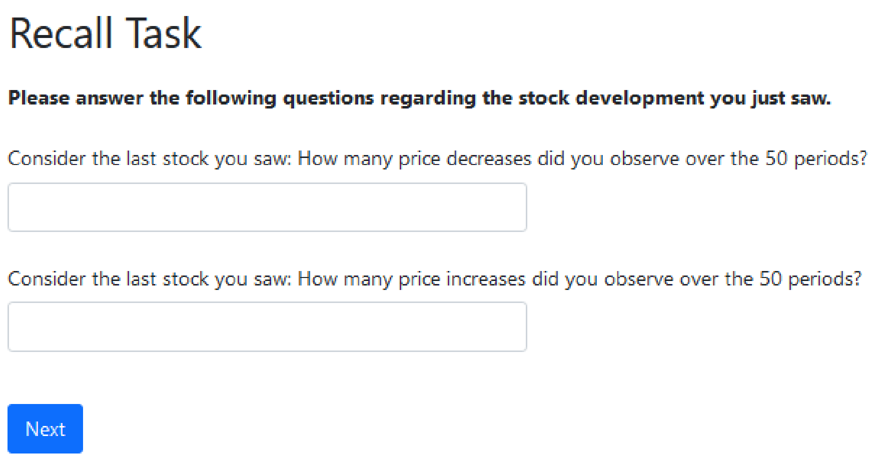


Figure B7: Recall Questions Page 2

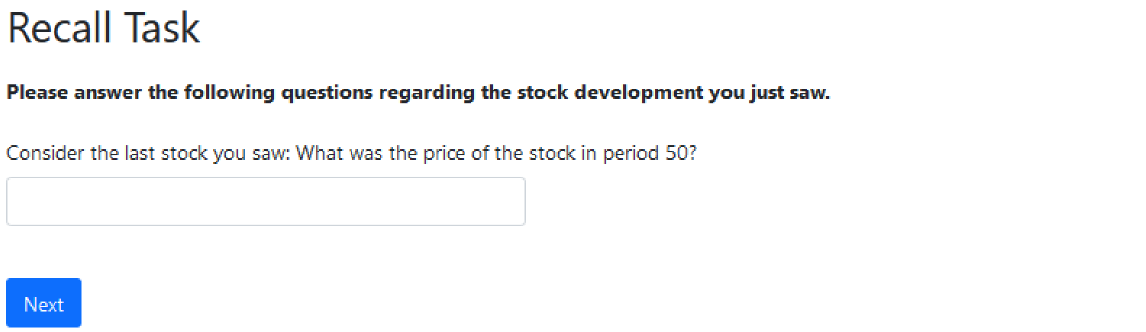
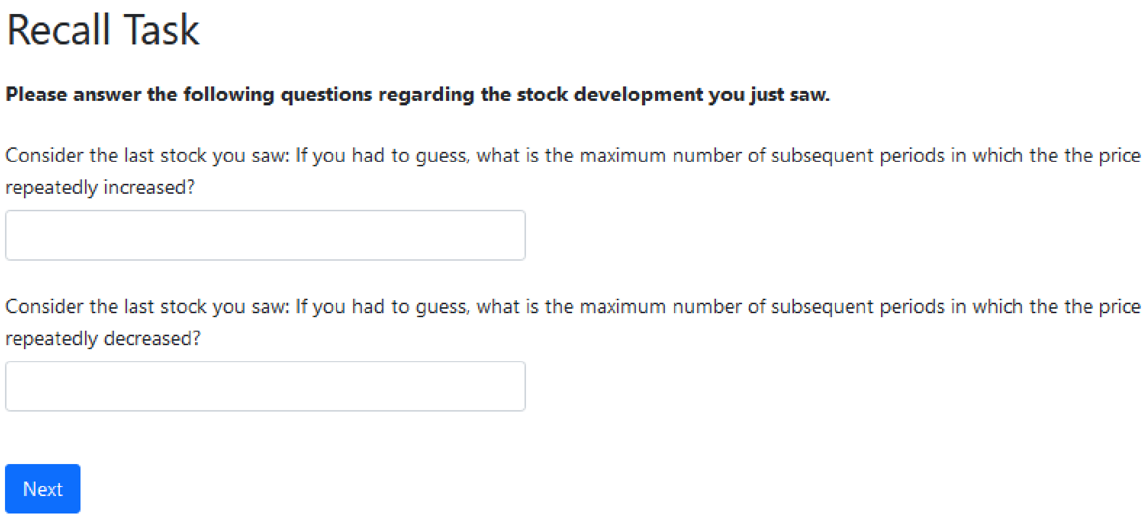


Figure B8: Recall Questions Page 3



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

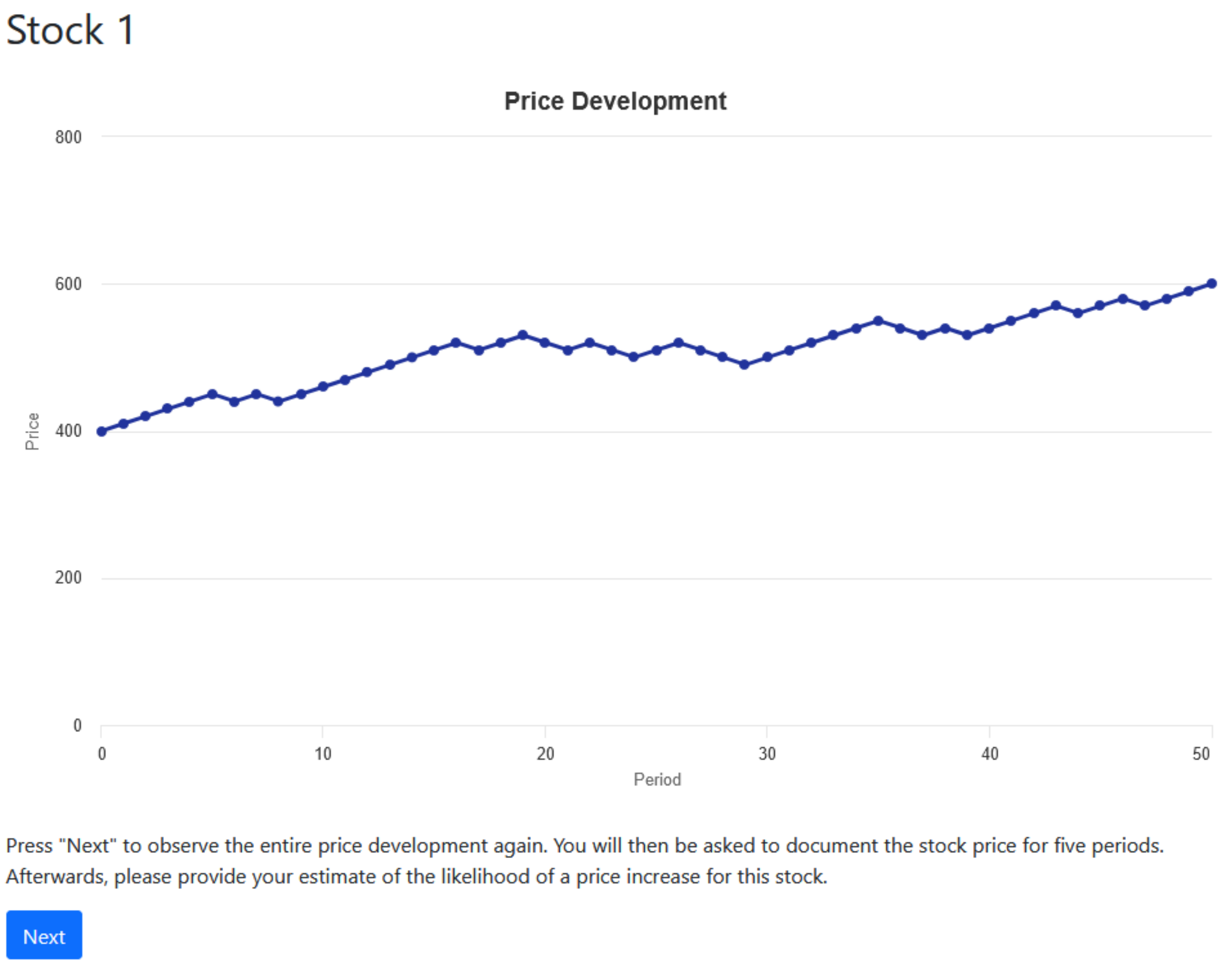
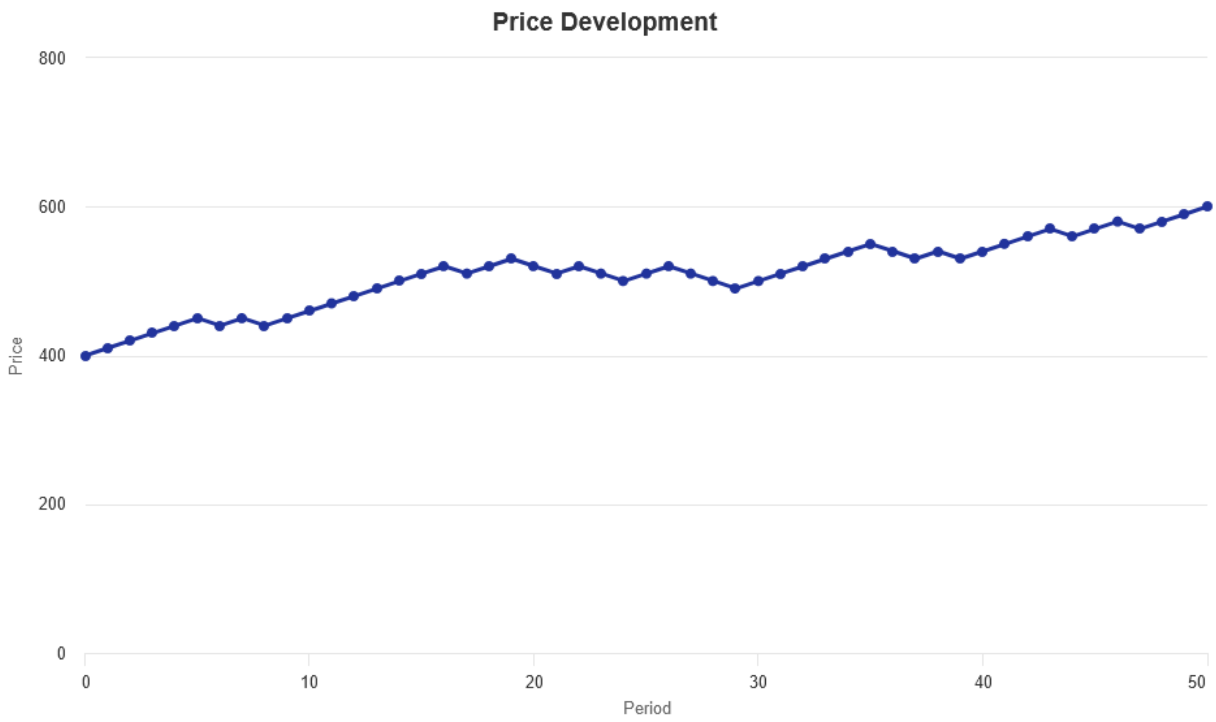


Figure B10: Price Identification

Stock 1



Please identify the stock price for the following five periods:

Period 21

Period 50

Period 34

Period 7

Period 16

Next