Stories, Statistics, and Memory*

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Abstract

For many decisions, we encounter relevant information over the course of days, months or years. We consume such information in various forms, including stories – qualitative content about individual instances – and statistics – quantitative data about collections of observations. This paper proposes that information type – story versus statistic – shapes selective memory. In controlled experiments, we document a pronounced story-statistic gap in memory: the average impact of statistics on beliefs fades by 73% over the course of a day, but the impact of a story fades by only 32%. Guided by a model of selective memory, we disentangle different mechanisms and document that similarity relationships drive this gap. Recall of a story increases when its qualitative content is more similar to a memory prompt. Irrelevant information in memory that is similar to the prompt, on the other hand, competes for retrieval with relevant information, impeding successful recall.

Keywords: Memory; Belief Formation; Stories; Narratives; Statistical Information.

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1 Introduction

People accumulate a wealth of information over the course of time, ranging from stories – qualitative descriptions of individual instances – to statistics – collections of information shown in numbers.[1] However, when making decisions, people may remember only a subset of all relevant information. In this paper, we examine the nature of such selective memory and its influence on the evolution of beliefs. We hypothesize that people are more likely to successfully remember stories than statistics, meaning that their beliefs are more persistently influenced by information they receive in the form of stories.

To study the temporal evolution of beliefs in response to different types of information, we run a series of tightly controlled, pre-registered experiments. In our baseline experiment, a hypothetical product or venue has received a number of reviews, each either positive or negative. We randomize what people learn about the number of positive reviews. In the *Statistic* condition, respondents receive quantitative information about the number of positive reviews in a randomly drawn subsample of reviews. In the *Story* condition, respondents obtain information about a randomly drawn single review alongside qualitative content describing the experience underlying the review. In a third condition, respondents receive no additional information. Our main outcome of interest are participants' incentivized beliefs about whether another randomly drawn review is positive. Each participant completes three independent scenarios about different products and venues, and is assigned to each information condition once. To examine the role of memory, we elicit beliefs from participants twice: immediately after receiving the information (the *Immediate* condition) and again following a one-day delay (the *Delay* condition). The temporal structure is crucial to our design as there are numerous differences between stories and statistics that could result in different beliefs; however, any such differences *not* arising from memory constraints are accounted for by the immediate belief update. Therefore, since no new information is received in the interim, any change in stated beliefs over time must, by design, be due to memory.

We document that, in line with imperfect memory, average beliefs partially revert to the prior as time passes. This temporal decay in beliefs emerges for both types of information. Our main finding is a pronounced story-statistic gap in the evolution of beliefs: the effect of stories on beliefs decays less strongly than the effect of statistics. Pooling all statistics and stories presented in our baseline study, we find that, on average, the magnitude of belief reversion from the immediate update towards the prior is more than twice as large for statistics (73%) as for stories (32%). In fact, we find that the average belief impact (the difference between a stated immediate or delayed belief and the induced prior) is larger for statistics than stories in *Immediate*, but smaller in *Delay*.

[1]This is the Oxford dictionary's definition of a statistic.

This means that the relative magnitudes of belief impact *flip* over time: statistics are, on average, interpreted as more informative in the moment and shift beliefs more strongly, but as time passes this effect reverses and the effect of stories on beliefs is larger. To provide direct evidence on the role of selective memory, we use a free recall task in the follow-up survey. We find that participants are approximately twice as accurate at recalling the correct type and direction of the information for the scenario in which they received a story than for the one in which they received a statistic.

Additional experiments demonstrate the robustness of our findings in a setting where respondents receive stories with qualitative content that is known to be uninformative. This allows us to compute the Bayesian benchmark based on the quantitative information contained in stories and statistics, respectively. Our experiments replicate our previous findings and establish that immediate belief updates are fairly close to Bayesian benchmarks for both types of information. Moreover, we conduct an experiment which shows that adding uninformative qualitative content to statistical information also significantly decreases belief decay and increases accurate recall. This suggests that it is the qualitative features of stories that drive the story-statistic gap in memory.

To guide our investigation of underlying memory mechanisms, we propose a simple model of selective memory that adapts Bordalo et al. (2023a,c) to accommodate stories and statistics. Our framework follows canonical models of memory, where experiences are stored as memory traces in episodic memory. A central feature of episodic memory is its cue-dependent nature: the recall of memory traces depends on their relationship to a so-called memory cue. In our model, the memory cue originates from an experimental prompt. In our experiments this prompt consists of the name of the product and a belief question. The prompt evokes *semantic associations* that are related in meaning to it. The prompt and these associations constitute the memory cue. To illustrate this, consider a scenario from our experiment about a restaurant. The prompt in the "restaurant" scenario is connected in meaning to concepts such as dinner, food and drinks, all of which are part of the cue. Given this memory cue, recall is stochastic: the decision-maker either recalls the relevant target memory or they accidentally recall an irrelevant, non-target memory. Whether a relevant or an irrelevant memory is retrieved is governed by two similarity relationships. The more similar a target memory trace is to the memory cue, the higher the chances of retrieving it. The more similar non-target memory traces are to the memory cue, the higher the chances of failing to retrieve the target and accidentally retrieving an irrelevant memory. This latter mechanism is referred to as *interference*.

Our simple framework makes three testable predictions about the likelihood of successful recall and the temporal decay of the initial belief movement induced by a piece of information. First, it predicts a story-statistic gap: stories are more likely to be successfully retrieved than statistics and are subject to less belief decay. This is because –

unlike statistics – stories include qualitative content that is related in meaning and thus similar to the prompt itself. Second, our model predicts that increasing cue-target similarity by adding elements to an experimental prompt that are related in meaning to a given piece of information increases recall likelihood and decreases belief decay when presented with that prompt. Third, the model implies that increasing the similarity between a cue and non-target information compromises the likelihood of successful recall and increases belief decay. Specifically, a non-target story that is related in meaning to the prompt makes it more likely that it will accidentally be retrieved, thereby increasing interference.

We develop experimental tests of the model's predictions. First, we consider the core mechanism from our model driving the story-statistic gap in memory: similarity between the target memory and the cue. Intuitively, a story might be particularly likely to be retrieved when its content is semantically related to the cue. On the other hand, for statistics, there is generally no semantic relationship to cues, since numbers are not typically related in meaning to specific concepts. To investigate the relevance of cue-target similarity, our mechanism experiment varies the similarity between the prompt and the story content. We document that the more similar the prompt is to the story content, the higher the accuracy of recall. Second, to test the model's prediction that similarity of irrelevant information to the cue shapes recall, we conduct an experiment that varies the similarity of the prompt to non-target stories. Consistent with the model's prediction, higher similarity of non-target stories to the prompt decreases recall and the persistence of belief impact of the target information. These results imply that in environments where many similar but conflicting stories circulate, stories lose their edge over statistics as a communication device. Taken together, our mechanism experiments highlight the importance of both cue-target similarity and interference. Our findings suggest that to persistently shape beliefs, effective communication should focus on qualitative features that are strongly semantically associated with the prompt the audience will likely encounter in the future.

We conclude by examining the relative importance of two potential margins of selective memory: first, people may fail to retrieve any relevant memories for a given scenario; second, people may successfully recall relevant memory traces but only partially recover the original information content. For example, people may remember that the majority of reviews were positive, but not what exact fraction were positive. To connect the magnitude of belief impact to different recall patterns, we jointly examine our recall and belief data. We document that conditional on correct recall, there remains virtually no story-statistic gap. These analyses provide an empirical foundation for modeling selective recall as primarily arising from retrieval failures rather than from distortions in retrieved content.

Our work relates to a nascent literature on stories and narratives in economics (Shiller, 2017, 2020; Michalopoulos and Xue, 2021; Andre et al., 2022a,b; Kendall and Charles, 2022; Morag and Loewenstein, 2021; Barron and Fries, 2023; Graeber et al., 2024a,b). This literature mostly focuses on the persuasive effects of narratives in moral or political domains (Bénabou et al., 2018; Eliaz and Spiegler, 2020; Bursztyn et al., 2023a,b; Alesina et al., 2023). A related literature in psychology and management studies the power of stories in influencing people (Fryer, 2003; Monarth, 2014; Bruner, 1987; McAdams, 2011). We add to the literature by (i) comparing the effect of stories to that of statistics over time, and (ii) providing systematic, theory-guided evidence on mechanisms with a focus on the role of qualitative information. Our evidence highlights one mechanism by which narratives are effective: they promote recall and thus more easily come to mind at the time of decision-making.

Our work also ties into a growing literature on the role of experiences, attention and memory in economics (Bordalo et al., 2020a, 2021; Gennaioli and Shleifer, 2010; Bordalo et al., 2020b, 2023b; Malmendier and Nagel, 2011, 2016; Link et al., 2023). The model heavily builds on Bordalo et al. (2023a,c), who provide theoretical frameworks in which agents form beliefs by retrieving experiences from memory based on similarity and interference. Enke et al. (2023) empirically study the role of associative memory for belief formation and show that it can give rise to overreaction to news. In contrast to our focus on the decay of belief impact over time, Enke et al. (2023) examine the extent to which the strength of immediate updating in response to new signals is influenced by the history of previous signals. Afrouzi et al. (2023) experimentally study the role of working memory in forecasting experiments. A series of recent papers also provide evidence on the role of associative recall in field settings, e.g., in finance (Charles, 2022; Jiang et al., 2022; Kwon and Tang, 2023) and the labor market (Conlon and Patel, 2022). Our paper strongly suggests that people do not continuously update their beliefs every time they receive a piece of information, but instead, they partly construct them on-the-fly, consistent with a growing body of evidence on cue-dependent belief formation (Andre et al., 2022a; Bordalo et al., 2021; Enke et al., 2023; Bordalo et al., 2023a). Our paper differs from this previous literature in its focus on how different types of information, statistics versus stories, shape beliefs over time.

More broadly, our work builds on extensive psychology literature on memory (Schacter, 2008; Kahana, 2012; Baddeley et al., 2020). Some previous work in psychology directly relates to the recall of stories, though with a particular focus on the role of scripts (Brewer and Treyens, 1981; Mandler, 1984; Schank and Abelson, 1977; Heath and Heath, 2007), emotions (Kensinger and Schacter, 2008) and mental imagery (Shepard and Cooper, 1986; Standing, 1973; Shepard, 1967). Bower and Clark (1969) document that students' ability to remember a list of words strongly increases when instructed to create a coherent narrative that contains all of the words.[2] These papers differ from ours in a number of ways. First, they focus on studying the recall of word lists, but do not measure beliefs nor track their evolution over time. Second, they do not compare the dynamics of belief formation based on statistics versus stories. Finally, these experiments do not aim to tightly identify underlying cognitive mechanisms, such as the role of cue-target similarity or interference, which are crucial ingredients for models of cue-dependent memory (Bordalo et al., 2023a,c).

This paper proceeds as follows: in Section 2, we outline a simple model of selective memory that formalizes mechanisms driving differences in the recall of story versus statistics. Section 3 presents experiments which demonstrate the existence and robustness of a story-statistic gap in memory. Section 4 describes our evidence on mechanisms. In Section 5, we provide a decomposition of the story-statistic gap and Section 6 discusses the implications of our findings.

2 A Model of Selective Memory

2.1 Setup

We outline a model of memory that adapts Bordalo et al. (2023a,c) to formalize cue-dependent recall and belief formation for stories and statistics. The model setup mirrors our experimental paradigm. Consider a decision-maker (DM) who learns about the reviews a specific product or venue has received. There is a population of N reviews, each of which is either positive or negative. The DM enters with a uniform belief over the number of positive reviews among N (ignorance belief). There are two periods. In the first period, the DM may receive additional information about the reviews of the product, either in the form of a story or a statistic. We define a statistic as a randomly drawn subset n of N that includes k positive and $n-k$ negative reviews. For our baseline setup, we define a story as a statistic of $n = 1$ complemented with additional non-quantitative content, akin to an anecdote about a single review.[3] In the second period, the DM receives no additional information. In both periods, the DM states a belief that a randomly drawn review from N is positive.

Over the course of the experiment, the DM faces three scenarios, each one about a different product or venue. Across these three scenarios, the DM receives one story, one statistic, and once no additional information.

[2]This relates to techniques for memory enhancement, which use visualizations of familiar spatial environments to improve the recall of information, commonly referred to as memory palaces or method of loci (Foer, 2012).

[3]However, note that the addition of qualitative content is, in principle, independent of the sample size of the corresponding statistic, which we explore experimentally in Section 3.5.

2.2 Similarity and Recall

In canonical models of memory, personal experiences are stored in episodic memory (Kahana, 2012). We assume that the DM's episodic memories are organized in a memory database M. Each element of M is a memory trace m that encodes one experience. A trace is a vector of $F \geq 1$ features with values in $V_1 \times \cdots \times V_F$. Some sets of possible values V_f contain the null value $\varnothing$ indicating the absence of a feature. Recall is cue-dependent, which means that recall is initiated by an external trigger that may be a situation, question or specific event. We represent a cue in the same way as memory traces, as a vector of length F with entries in $V_1 \times V_2 \times \cdots \times V_F$. Given any database of traces and any cue, recall is stochastic and governed by the similarity relationships between the cue and the memory traces. We define a similarity measure over any two traces or cue vectors, x_1 and x_2,

$$S(x_1, x_2) : \prod_{i=1}^{F} V_i \times \prod_{i=1}^{F} V_i \to [0, 1],$$

and require that it is symmetric, increasing in the number of features that share the same value, equals 1 if and only if $x_1 = x_2$, and equals 0 if and only if no feature is shared. The probability of recalling a specific target trace m^* when cued with c is given by

$$r(m^*, c) := \frac{S(m^*, c)}{\sum_{m \in M} S(m, c)}. \tag{1}$$

The probability of recall is jointly governed by the *cue-target similarity* in the numerator, i.e., the similarity between the cue and the target trace m^*, and *interference* in the denominator, i.e., the similarity between the cue and all other memories. The likelihood of successfully recalling the target trace increases in the cue-target similarity. On the other hand, higher interference yields a higher likelihood of accidentally retrieving an irrelevant memory trace.

2.3 Memory Traces and Cues

Memory traces. In the baseline experiment, there are three scenarios: a bicycle, a restaurant and a video game, creating three corresponding memory traces. We assume the following vector structure for memory traces: the first dimension identifies the scenario, i.e., $V_1 = \{\text{bicycle}, \text{restaurant}, \text{video game}\}$ in the baseline experiment. The second entry encodes the number of reviews n that the DM learns about, i.e., $V_2 = \{0, \ldots, N\}$, with 0 implying that no additional information was received. The third entry carries the number k of positive reviews among the n reviews provided, i.e., $V_3 = \{0, \ldots, N\}$, with $k \leq n$. All additional entries of a trace represent the non-quantitative content provided through a story. These dimensions encode everything that was mentioned in the qualitative content of the scenario. We refer to this set of features by V^{qual} and do not constrain its structure further. V^{qual} is large enough to encode any possible story across all scenarios, and each feature takes the null value or 1, indicating the absence or existence of that feature.[4] For any given trace m, we refer to a realization of the qualitative features as $V^{\text{qual}}(m)$. Note that here, we focus on how memory traces encode the content that was explicitly provided in a scenario. In addition, standard memory models assume that episodic memories also encode the context in which an experience was made, such as the time of day or weather. Such context could be readily accommodated by $V^{\text{qual}}(m)$, but because most context is plausibly shared across the experiences associated with different scenarios in the experiment, it is largely irrelevant for our purposes besides introducing a base-level similarity between all traces. This is why our exposition of the trace structure focuses on content rather than context.[5]

Memory traces associated with stories and statistics both contain entries in the first three dimensions. The key difference between them is that stories provide additional non-quantitative content, captured by $V^{\text{qual}}(m)$. A memory trace for a scenario has at least one feature present in V^{qual} if a story was received, but none if a statistic or no additional information was received in the baseline experiment.

In what follows, we denote the treatment type of a memory trace (statistic, story, or dummy) in superscript and the product type in subscript. Given the above assumptions, a statistic conveying that 3 out of 7 reviews for the scenario bicycle were negative forms the following trace in the memory database:

$$m^{\text{statistic}}_{\text{bicycle}} = \left(\text{bicycle},\ 7,\ 4, V^{\text{qual}}(m^{\text{statistic}}_{\text{bicycle}})\right) \quad \text{with} \quad V^{\text{qual}}(m^{\text{statistic}}_{\text{bicycle}}) = (\varnothing, \varnothing, \ldots)$$

A story about a negative review at a restaurant would enter the database as

$$m^{\text{story}}_{\text{restaurant}} = (\text{restaurant},\ 1,\ 0, V^{\text{qual}}(m^{\text{story}}_{\text{restaurant}}) \quad \text{with} \quad V^{\text{qual}}(m^{\text{story}}_{\text{restaurant}}) \neq (\varnothing, \varnothing, \ldots),$$

i.e., $V^{\text{qual}}(m^{\text{story}}_{\text{restaurant}})$ does not only contain null entries. In particular, $V^{\text{qual}}(m^{\text{story}}_{\text{restaurant}})$ contains some entries that represent non-quantitative attributes of the story; for example, that the food was stale or the waiter was unfriendly. The trace produced in a scenario about a video game where no additional information was provided would be encoded

[4]For modeling reasons, all memory vectors share the same dimensionality, i.e., all have $V^{\text{qual}} + 3$ entries.

[5]It is possible that encoding depends on the informativeness of the information. We abstract from such differences for the sake of simplicity.

as

$$m^{\text{dummy}}_{\text{video game}} = (\text{video game}, 0, 0, V^{\text{qual}}(m^{\text{dummy}}_{\text{video game}})) \quad \text{with} \quad V^{\text{qual}}(m^{\text{dummy}}_{\text{video game}}) = (\varnothing, \varnothing, \ldots).$$

Cues. Retrieval is triggered by a memory cue, which in our setup originates from a prompt in the experiment. The prompt contains the question about a randomly drawn review of the product as well as the scenario name. Unlike the prompt, which is an experimentally controlled feature, the cue is a theoretical construct. We formalize the cue as invoking a vector c that contains both the prompt as well as a (potentially large) set of *semantic associations* with the prompt. These are connections and relationships that words or concepts have in common with the prompt based on their meanings (McRae and Jones, 2013). The intuition is that the prompt triggers connected concepts that automatically come to mind. For instance, when reading the word "restaurant," natural semantic associations may be "food," "service," or "atmosphere." We abstain from modeling the structure of semantic associations, which is outside the scope of our paper. Instead, we only assume that for any scenario s, the experimental prompt evokes a cue-vector c_s that includes non-null features in V^{qual}.

Moreover, we assume that a story is actually *about* the scenario at hand; in a natural, relevant story, at least parts of its content are semantically associated with the scenario. The story relates in meaning to the underlying situation. As a result, the memory trace formed by reading a story includes some features that overlap with what the DM semantically associates with the prompt alone. Formally, there is at least one shared feature between $V^{\text{qual}}(m^{\text{story}}_s)$ and $V^{\text{qual}}(c_s)$. To illustrate, consider a story in which stale sushi was served at a restaurant. This could be represented in the memory trace by a feature encoding (bad) food. Being prompted with the word "restaurant" automatically triggers thoughts of food, so that the cue and the story trace share the feature "food."

2.4 Belief Formation

The DM forms a belief about whether a randomly drawn review in a given scenario is positive. We remain agnostic about how exactly beliefs are formed given the information that is presented or recalled and hence formalize a very general updating rule that only assumes time-invariance.[6] All the distortions we study experimentally are captured by the recall process.

Entering with an ignorance belief, the DM (potentially) receives additional information on a scenario in the first period. They form a posterior belief and, at the same time, store a single memory trace m^* that follows the structure outlined above. In the second

[6]This general updating rule nests Bayesian updating.

period, the DM is again prompted to state their belief. Rather than recalling their first-period posterior directly, we propose that the DM again enters this decision with their ignorance belief, and may or may not remember the additional information received in the meantime. In terms of timeline, this can be thought of as the DM coming in with a flat belief, accumulating information over time, and then trying to remember this past information in the moment they face a decision. The prompt generates a cue c, which gives the agent a chance $r(m^*, c)$ to recall the target trace m^* and with it all the relevant additional information from the scenario. If any other trace than the target trace is retrieved, the agent notices their mistake and discards it. Successful recall leads to a posterior belief in the second period that is identical to the first-period belief, whereas failed recall means the agent reverts to their ignorance belief.

Notation. For a given scenario, the DM's belief in period t is π_t and the stated belief is $\hat{\pi}_t$. The ignorance belief is denoted by π_0. We define a general updating rule Φ as a function taking the ignorance belief π_0 and an information set I and yielding a posterior belief π_1.

Stated belief absent additional information. We assume that if the DM does not have access to additional information, the posterior equals the ignorance belief, i.e., $I = \emptyset \implies \pi_0 = \pi_1$. The experiment implements a scoring rule under which reporting the mean maximizes payoffs:

$$\hat{\pi}^{no\ info} = \mathbb{E}[\pi_0] = \frac{1}{2}$$

Stated beliefs with additional information. The DM forms a belief update using the updating rule Φ, ignorance belief π_0, and the additional information I to arrive at belief π^{info}. Given the incentive structure the DM then states their expected value $\hat{\pi}^{info} = \mathbb{E}[\pi^{info}]$.

Recall and belief decay. We formalize belief decay as the absolute value of the difference between the beliefs formed in the second and first period. Note that if recall is successful, beliefs are stable so that $\hat{\pi}_2 = \hat{\pi}^{info} = \hat{\pi}_1$, and if recall fails, then $\hat{\pi}_2 = \hat{\pi}^{no\ info}$. The expected second-period belief conditional on period 1 is hence $\mathbb{E}[\hat{\pi}_2 \mid \hat{\pi}_1] = r(m^*, c)\hat{\pi}_1 + (1 - r(m,^* c))\frac{1}{2}$. Belief decay is governed by the probability of recall scaled by the distance of the first-period belief to the ignorance belief:

$$\mathbb{E}[|\hat{\pi}_2 - \hat{\pi}_1| \mid \hat{\pi}_1] = (1 - r(m^*, c)) \cdot |\frac{1}{2} - \hat{\pi}_1| \tag{2}$$

Discussion. In our model, beliefs are proportional to recall. Indeed, there are only two possible beliefs people hold in our model, even after a delay: the posterior belief formed in period 1 and the ignorance belief. We consider this feature a strong simplification for the purpose of demonstrating the key implications of our model. We acknowledge that belief formation data in practice typically exhibits noise and is unlikely to be fully explained by our model that predicts a bi-modal distribution. Our analyses in Section 5, however, demonstrate that a large majority of often up to 80% of our observations are indeed captured by either no belief decay or full reversion to the ignorance belief, justifying our model simplification. A more complete model would incorporate noise in the belief formation or retrieval process, along the lines of, e.g., Enke and Graeber (2023). Notice that, under our model, which only accommodates two possible updates, we cannot identify the degree of belief decay (equation 5) at the individual level, but only across subjects. This, however, neither constrains our empirical analyses much nor does partial belief decay at the individual level play a large role in our data, as discussed in Section 5.

2.5 Predictions

Our simple framework makes three main predictions that guide our empirical analysis. The first one establishes the existence of a story-statistic gap. All derivations and additional predictions are relegated to Appendix G.

Prediction 1. *(Story-Statistic Gap.) The likelihood of successful recall is higher for stories than for statistics. Conditional on first-period beliefs, belief decay for stories is lower than for statistics.*

Intuitively, recall of stories is more likely than that of statistics because the additional, non-quantitative content is semantically associated with the scenario, and thus stories exhibit a higher cue-target similarity than statistics. A higher likelihood of successful recall induces less belief decay in expectation.

The next two predictions concern the building blocks of the recall mechanism in Equation (1): cue-target similarity and interference. As to the former, we obtain the following implication on the impact of changing the prompt in a way that increases the number of shared features.

Prediction 2. *(Cue-Target Similarity.) Changing the prompt to invoke semantic associations that have a larger overlap with the target memory trace raises cue-target similarity. This increases the likelihood of successful recall and decreases belief decay.*

Next we consider the role of interference. Interference is governed by the similarity of non-target memories m to the cue c, $S(m,c)$. The higher the similarity between the qualitative content of non-target traces and a given target cue, the more pronounced are forgetting of the target trace and belief decay. To illustrate, assume that there are two scenarios, one about a food truck and one about an amusement park. Consider a story provided in the amusement park scenario that is either about the rides or about the food consumed in the park. The latter story is naturally more closely related in meaning to the other scenario (food truck) than the former story. The similarity between the given scenario (food truck) and non-target traces (food in the amusement park) induces a higher probability of accidentally retrieving the memory created for the amusement park in recall about the food truck. In terms of the model, this is reflected in an overlap between $V^{\text{qual}}(m_p^{\text{story}})$ and $V^{\text{qual}}(c_q)$.

Prediction 3. *(Interference.) All else equal, increasing the similarity between a story in scenario p and a cue for another scenario q decreases the likelihood of successful recall and increases belief decay in q.*

3 The Story-Statistic Gap in Memory

3.1 Baseline Design

Our baseline design is guided by the following objectives: (i) panel data on beliefs that allow us to study the evolution of beliefs over time without new information arriving in the meantime; (ii) a measure of immediate updating that captures any differences in the effects of stories and statistics that are not memory-related; (iii) a setting in which information both in the form of statistics and stories is common; and (iv) an incentive-compatible belief elicitation. Table A.7 provides an overview of all experiments.

Task structure and timing. There are three different hypothetical scenarios, each one about some product or venue.[7] Any given product or venue has received an overall number of reviews, with each review being either positive or negative. In the model in Section 2 we assume that the decision-maker enters with an ignorance belief. To fix this ignorance belief in our experiments, we truthfully inform respondents that the actual number of positive reviews would be randomly drawn from a uniform distribution, independently for each scenario, inducing a uniform prior. For each scenario, participants then receive either a piece of additional information or no additional information, and are

[7]We chose hypothetical scenarios to prevent that relevant additional information can be gathered outside of the experiment.

subsequently asked to state their guess.[8] Our main outcome of interest are respondents' incentivized beliefs about the likelihood that a randomly selected review is positive.[9] To examine the role of memory, we elicit beliefs twice: once immediately upon receiving the information (condition *Immediate*) and once one day later (condition *Delay*).

Stories versus statistics. We vary the type of additional information participants are exposed to within-subject and across scenarios. For each scenario, participants receive either statistical information (condition *Statistic*), anecdotal information (condition *Story*) or no further information. Randomization is blocked such that across scenarios, each individual receives one story, one statistic, and once no additional information. Moreover, the order of scenarios is randomized and each individual receives one positive signal and one negative signal.[10]

We conceptualize statistics as quantitative information about many reviews. In contrast, we define stories as quantitative information about a single review coupled with qualitative content. Thus, stories and statistics differ along two margins in our baseline setup: first, statistics describe multiple data points, while stories are about only one data point. The second difference is the presence of qualitative content.[11]

Our design closely adheres to this basic taxonomy. Statistical information is communicated as the number of positive reviews for a randomly selected subsample of the population. The fraction of positive reviews is randomly determined, creating variation in the extremity of statistics. Below is an example of how statistical information is communicated:

> *13 of the reviews were randomly selected. 4 of the 13 selected reviews are positive, the others are negative.*

A story provides information about whether a single randomly selected review is positive or negative, plus a qualitative description of that review. The description consists of

[8]We included the no information treatment as it adds a natural additional source of uncertainty, namely uncertainty about whether the respondent actually received relevant information in a scenario. Moreover, the treatment allows us to verify that our respondents understand the setting by checking whether, absent any additional information, they state a belief of 50%.

[9]The belief elicitation is incentivized using a binarized scoring rule (Hossain and Okui, 2013) with a prize of \$30. The precise payment formula is: Probability of winning \$30 (in percent) $= 100 - 1/100$ (estimate (in percent) - Truth)^2, where truth = 100 if the randomly selected review is positive, and 0 if not. The binarized scoring rule is incentive-compatible, even in the presence of risk aversion. Danz et al. (2022) document that empirically, the binarized scoring rule can lead to systematic bias in reported beliefs. Notice that, even if such bias were present in our experiment, it would not compromise our identification which relies on the comparison of beliefs between *Immediate* and *Delay* for stories and statistics. Moreover, all of our findings are supported by evidence on recall, which is immune to the concern about scoring rules.

[10]Appendix D provides details on the implementation of the randomization.

[11]Note that in principle, qualitative content could also be added to statistical information. While we maintain that a natural distinction between stories and statistics is that they tend to differ in sample size, Section 3.5 explores the role of adding qualitative content to statistics of fixed sample sizes larger than one.

six to seven sentences recounting the experience underlying the review. We randomize the valence of the qualitative content described in the review between participants. For our main analysis, we focus on stories in which the valence of the qualitative content matches the overall review rating. Below is a shortened example of a story accompanying a negative review about a restaurant:[12]

> *One of the reviews was randomly selected. The selected review is negative. It was provided by Justin... The raw fish looked stale and the sushi rolls were falling apart on the plate... The service was poor: his waiter was rude, not attentive and the food was served after a long wait... As they left the restaurant, Justin was very annoyed and thought to himself "I definitely won't be back!"*

A notable feature of stories is that they are not easily accommodated in a Bayesian belief updating framework because the informational content of qualitative statements cannot be quantified in a fully objective way.[13] For instance, in the example above, the qualitative description of the food arguably allows participants to infer that other reviewers may have had similar experiences. Because we cannot determine the normatively optimal Bayesian inference from such qualitative information, we rely on our *Immediate* belief measurement to capture how informative participants *perceive* each story to be.[14] Note that this approach is also not reliant on the assumption that people form their beliefs in accordance with Bayes' rule, which may be commonly violated in practice (Enke and Zimmermann, 2019; Graeber, 2023; Enke, 2020; Martínez-Marquina et al., 2019; Hartzmark et al., 2021; Ba et al., 2023).

Prompt. A critical design feature is the prompt, which in our setup consists of the scenario name and the subsequent belief question. The prompt hence always specifies the product or venue, and then elicits beliefs about whether a randomly drawn review for that product or venue was positive or negative. Specifically, on the screen of the belief elicitation, both in condition *Immediate* and in condition *Delay*, respondents first learn about the product or venue that we elicit beliefs about. For example, in the case of the restaurant they learn that *"A restaurant has received 19 reviews."* To measure beliefs, we use the following instructions:

> *Out of all the 19 reviews, another review was randomly chosen, where each of the 19 reviews was equally likely to be selected. What do you think is the likelihood (in %) that this review is positive?*

[12]Appendix C.1 reproduces all stories from the baseline experiment.

[13]In Section 3.4.1 we provide evidence from a setting in which we can cleanly compare belief movements to a Bayesian benchmark.

[14]Our approach therefore also accounts for possible differences in the credibility of the information provided in the *Statistic* versus the *Story* treatments.

Recall elicitation. We also provide direct evidence on recall of the additional information about product reviews received in the baseline survey.[15] To do so, after displaying the scenario name, we ask our respondents the following unincentivized open-ended question:

> *Please tell us anything you remember about this product scenario. Include as much detail as you can. Most importantly, please describe things in the order they come to mind, i.e., the first thought first, then the next one etc.*

Hand-coding scheme. To analyze the unstructured text data, we design and implement a hand-coding scheme (see all details in Appendix E). The hand-coding scheme records whether respondents mention the direction and type of information they encountered, and whether they correctly remember these characteristics. It also captures additional features, such as (i) whether respondents in the *Story* condition mention qualitative features, (ii) whether they correctly recall the exact statistical information, and (iii) whether they recall the belief they stated in the baseline survey. To ensure high quality of the hand-coded data, we proceed as follows. First, we instruct three research assistants on the coding scheme and conduct a series of practice rounds with them. Second, each open text response is independently coded by two of the research assistants. Any potential conflicts are resolved by the third research assistant. We find that the inter-rater reliability is high: for correct recall of type and direction, we find agreement in 94% of the cases.

Incentives. Participants were informed in advance that the survey consisted of two parts, with one day in between. We also told participants that the information they receive would be relevant for payoffs one day later. Participants were truthfully informed that the computer would randomly select 10% of participants to receive a bonus payment that would be based on their responses.[16] To avoid hedging between similar questions in the two parts, one of the three scenarios and one of the two parts for that scenario (immediate belief, delayed belief) were randomly selected to count for the bonus payment.

Comprehension checks. We implemented an attention check as well as extensive control questions to verify participants' understanding of the instructions. Participation in

[15]We randomized the order of the belief and recall elicitation. In additional studies that replicate our baseline findings with structured incentivized recall tasks instead of the open-ended question (see Section 3.4.1).

[16]We paid out close to $15,000 in bonuses across all of our data collections.

the survey required passing an attention check and answering all control questions correctly within the first two trials. These control questions ensure high levels of understanding of the payoff incentives as well as the signals and prior distribution of draws.

3.2 Data

Sample. We collected data for the baseline experiment on September 8 (baseline) and September 9 (follow-up) 2022. We recruited participants via Prolific, a survey provider commonly used in social science research (Peer et al., 2022). The average duration of the survey was about 9 minutes for the baseline, and 5 minutes for the follow-up. For the baseline, participants received a completion payment of $1.55 and for the follow-up they received 90 cents.

1,500 respondents completed wave 1 of our experiment. Out of those, 1,364 met the inclusion criteria and were invited for the follow-up survey.[17] 1,035 then completed the follow-up survey. After the pre-specified sample restrictions,[18] our final sample consists of 933 participants, corresponding to a completion rate of 68 percent. Given that the key treatment variation is within-person, the attrition rate is not a threat to the internal validity of our findings. For completeness, we report analyses on attrition rates in Appendix Table A.12.

Pre-registration. All experiments in this paper were conducted online and pre-registered on AsPredicted. The pre-registrations include the experimental design, hypotheses, analyses, sample sizes, and exclusion criteria. A link to each pre-registration is provided in Table A.7. The full set of instructions can be found on the following link: `https://raw.githubusercontent.com/cproth/papers/master/SSM_instructions.pdf`.

3.3 Baseline Results

Beliefs. As pre-registered, we start by analyzing stories with qualitative content that is consistent with the overall review rating, which is either positive or negative. The top panel of Figure 1 and Table 1 show the average belief impact in *Immediate* and *Delay*, pooling the data across scenarios and individuals. Belief impact is the signed distance between a stated belief and the prior (50%). For ease of exposition, we reverse-code the belief impact whenever the additional information implied a downward update, i.e.,

[17] We exclude observations of 52 participants who were affected by a technical error in the survey code in wave 1. When the drawn statistic corresponded to a share of 100% positive reviews, no numbers were displayed on the screen. Including these additional 52 participants leaves all results virtually unchanged, see Appendix A.8. The only other experiment affected by the coding error is Robustness Experiment 4.

[18] We pre-specified the exclusion of respondents who indicated having written down the information they received and those updating in the wrong direction in response to statistics.

belief impact is signed in the direction of the rational update. Beliefs in *Immediate* serve as a benchmark that captures any difference in the effect of stories and statistics that is not related to memory.

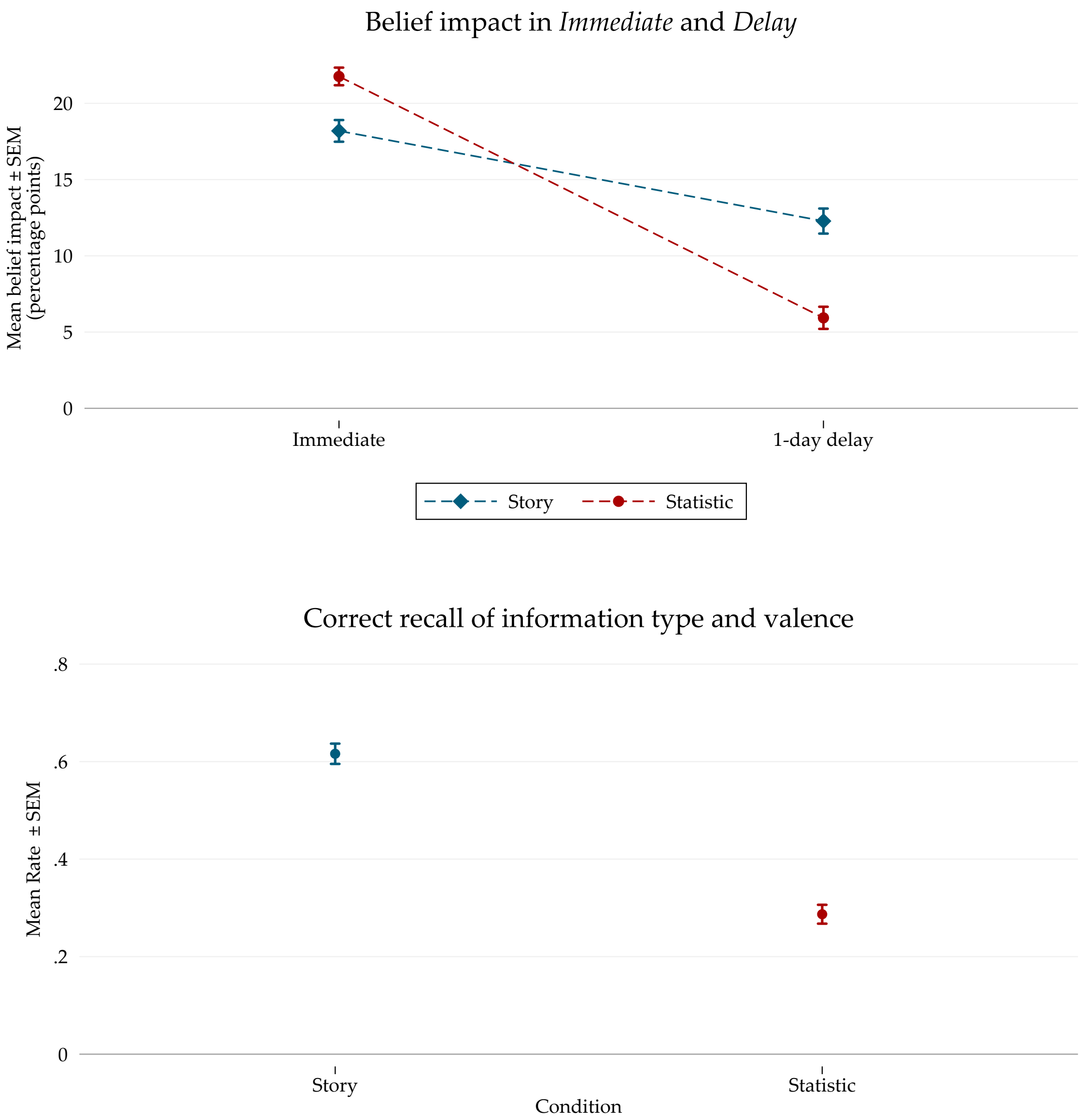


Figure 1: The story-statistic gap in the baseline experiment (933 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The red markers refer to statistics, while the blue markers refer to stories. The average Bayesian benchmark for statistics is 20.91 p.p., while the average Bayesian benchmark for stories is 18.71 p.p. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey, as measured with an open-ended recall question. Whiskers indicate one standard error of the mean.

The top panel of Figure 1 reveals that, in line with our hypothesis, the decay in belief impact over time is substantially lower for stories than statistics. This is confirmed by column (3) of Table 1. The difference-in-differences estimate of belief impact between *Immediate* and *Delay* is highly significant ($p < 0.01$).

We next consider point estimates of the belief impact in *Immediate*. The average belief impact in *Immediate* is larger for *Statistic* than for *Story*. On average, beliefs move by 21.76 p.p. (s.e. 0.58) for *Statistic* and by 18.19 p.p. (s.e. 0.71) for *Story*.[19] By contrast, for the *Delay* condition, the top panel of Figure 1 reveals that mean belief impact after one day is substantially more pronounced for *Story* than for *Statistic*. On average, belief impact was 5.93 p.p. (s.e. 0.73) in *Statistic* and 12.28 p.p. (s.e. 0.82) in *Story*. This divergence in belief impact in *Delay* is significantly different from zero ($p < 0.01$). Appendix Figure A.10 underscores these patterns in the cumulative distribution functions of belief impact in *Immediate* and *Delay*, separately for stories and statistics.[20]

Recall. It is conceivable that it may take some time for information to "sink in", and that the beliefs in *Immediate* are elicited before the information has been fully processed.[21] In that case, using the immediate belief as a benchmark may not adequately capture the maximal belief update. We address these concerns using direct data on accurate recall of the provided information.

To study recall, we examine the fraction of respondents who correctly recall both the type and the direction of the information they were provided, as measured in the open-ended recall question. The bottom panel of Figure 1 shows that correct recall is significantly higher for stories than for statistics ($p < 0.01$). The average correct recall is 61.61 percent for stories and 28.70 percent for statistics. This suggests that information delivered in the form of stories is more easily retrieved than statistical information. Moreover, the open-ended data reveal several other patterns: (i) A large fraction of respondents (44.91%) mention qualitative features from the story without specifically being prompted to do so; (ii) a very small fraction of respondents (1.32%) correctly recall and indicate the statistic they received; and (iii) only a negligible fraction (4.23%) mention the posterior belief they stated in the baseline wave. Note that this free-recall data provides a lower bound for whether people could recall each of these different features of

[19]The immediate belief impact is close to the (average) Bayesian benchmark for both statistics (20.91 p.p.) and stories (18.71 p.p.). Note that for stories, we only consider the quantitative information contained in the review to compute the Bayesian benchmark, i.e., we do not factor in the potential effect of the qualitative content provided. The experiment reported in Section 3.4.1 provides evidence from a setting where the Bayesian benchmark is well-defined also for stories.

[20]The figure also highlights that there is substantial heterogeneity in perceived informativeness of the story treatment as measured in the immediate condition. This likely arises from differences in the way respondents interpret the qualitative information provided in the story.

[21]In addition, there may be differences between stories and statistics in the extent to which participants rehearse the information they were provided with. Rehearsal cannot explain the findings of our mechanism experiments, presented in Section 4, which hold constant the target information respondents are exposed to.

Table 1: The story-statistics gap in memory

	Dependent variable:			
	Belief Impact			Combined Recall
Sample:	Immediate (1)	Delay (2)	Pooled (3)	Consistent (4)
Story	-3.57*** (1.24)	6.35*** (1.55)	-3.57*** (1.01)	0.33*** (0.04)
Delay			-15.8*** (0.92)	
Story × Delay			9.92*** (1.32)	
Control Mean	21.76	5.93	21.76	0.29
Observations	1094	1094	2188	1094
R^2	0.55	0.52	0.43	0.65

Notes. This Table uses responses from the *Story* and *Statistic* condition. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Story* takes value 1 for respondents who received a story for a given product, and zero otherwise. *Statistic* takes value 1 for respondents who received a statistic for a given product, and zero otherwise. Columns (1), (2) and (4) include respondents who received consistent stories. Column (3) pools *Immediate* and *Delay*. Columns (1) to (3) display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Column (4) displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the information they were exposed to in wave 1. This is because they were not explicitly prompted to recall any specific feature.

Heterogeneity by extremity of immediate update. Figure 2 illustrates the heterogeneity of delayed belief impact and correct recall by the extremity of the immediate update. The figure showcases little heterogeneity in correct recall by the extremity of the immediate belief update. For all levels of immediate updating, delayed belief impact and correct recall are higher for stories than for statistics.

Result 1. *There is a story-statistic gap in memory: over the course of one day, the effect of stories on beliefs decays less strongly than the effect of statistics. Stories have a stronger effect on beliefs than statistics in Delay, even though statistics have stronger immediate effects. Recall accuracy is substantially higher for stories than for statistics and does not depend on the strength of the immediate update.*

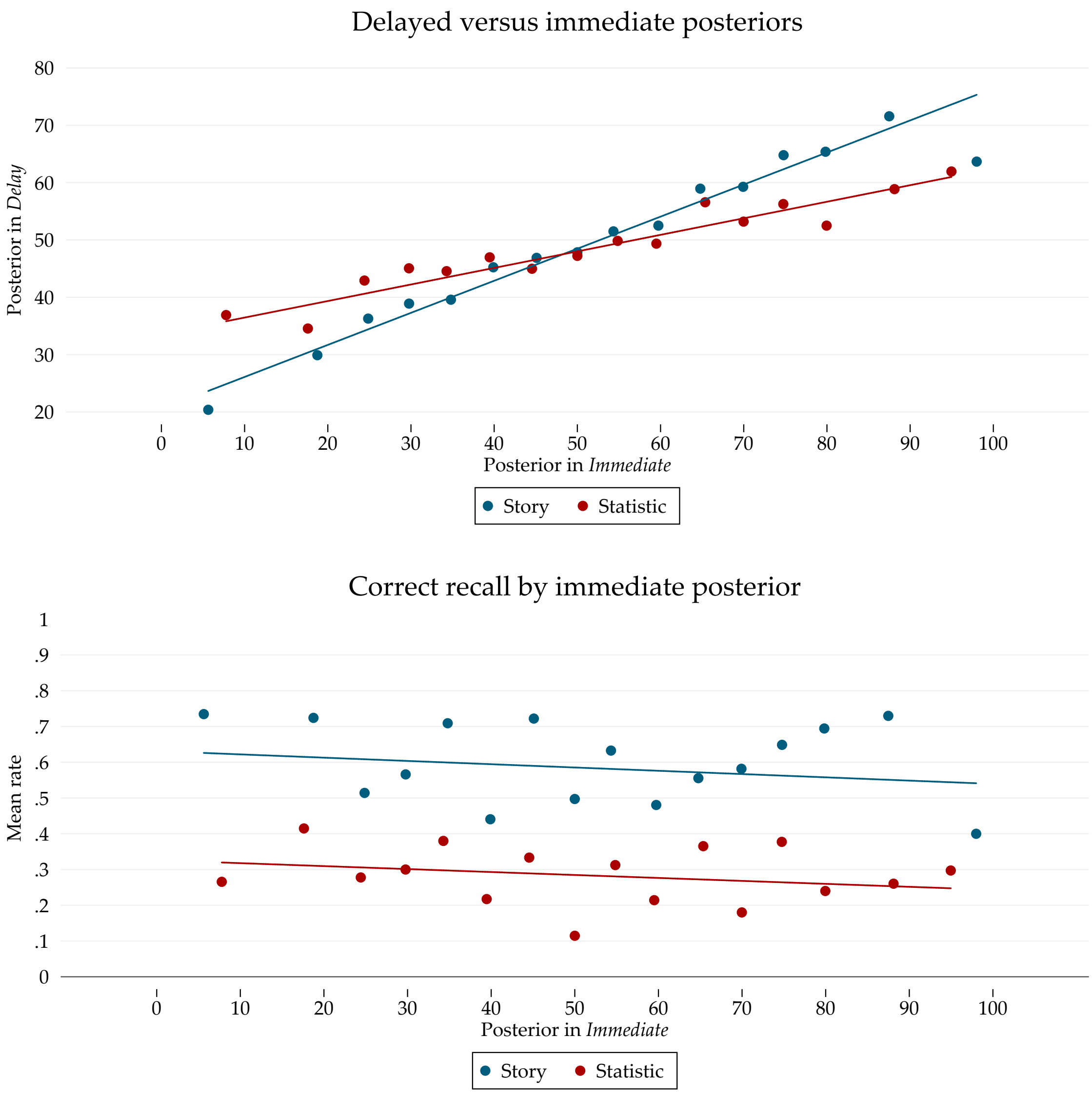


Figure 2: Heterogeneity by extremity of immediate update in the baseline experiment (933 respondents). The top panel displays binned scatterplots regressing beliefs in *Delay* (y-axis) on beliefs in *Immediate*, separately for conditions *Story* and *Statistic*. The bottom panel displays binned scatterplots regressing correct recall of the type and direction of information they received in the baseline survey in *Delay* (y-axis) on beliefs in *Immediate*, separately for conditions *Story* and *Statistic*. The red dots and line illustrate beliefs and recall for statistics, while the blue dots and line illustrate beliefs and recall for stories.

3.4 Robustness

3.4.1 Experiment with Uninformative Qualitative Content

Design. A possible concern with our baseline design is that, as discussed above, we cannot compute Bayesian benchmarks for the Story treatment. Respondents may interpret the qualitative content to be informative above and beyond the quantitative information. To deal with this concern, we conduct a robustness experiment which is identical to our baseline experiment except that it explicitly tells respondents that the qualitative content of the stories is uninformative, hence allowing for the computation of a Bayesian benchmark. We directly confirm that respondents understand this using an additional comprehension question. Appendix A.1 provides additional details.

Sample. We recruited 1,000 respondents for the baseline survey. 912 respondents qualified for the follow-up survey. After the pre-specified sample restrictions, our final sample consists of 714 respondents, corresponding to a completion rate of 78 percent.

Belief movement. Appendix Figure A.1 confirms our baseline finding: The decay in belief impact over time is significantly lower for stories than statistics ($p < 0.01$), as illustrated by column (3) of Appendix Table A.1.

We next consider point estimates of the belief impact in *Immediate*. Average belief impact in *Immediate* is larger for *Statistic* than for *Story*. On average, beliefs move by 21.91 p.p. (s.e. 0.49) for *Statistic* and by 19.21 p.p. (s.e. 0.51) for *Story*. The immediate belief impact is close to the average Bayesian benchmark for both statistics (22.07 p.p.) and stories (18.68 p.p.).[22]

For the *Delay* condition, belief impact is 8.57 p.p. (s.e. 0.62) in *Statistic* and 10.52 p.p. (s.e. 0.66) in *Story*. This difference in belief impact in *Delay* is significantly different from zero ($p < 0.01$).[23] These findings underscore that respondents in the *Story* condition hold delayed beliefs that are significantly closer to the Bayesian benchmark.

Incentivized structured recall To complement our open-ended measure of recall from the baseline experiment, we use an incentivized structured recall task in this robustness experiment. We ask respondents to indicate whether they (i) received information about a single review, including some additional anecdotal details about the reviewer and their experience with the product, (ii) multiple reviews, (iii) no information, or (iv) don't know.[24] Unless respondents indicate that they did not receive any information about this product, we additionally ask them to indicate whether the information they

[22]The difference between the two benchmarks might seem surprisingly small. Because a single review is either positive or negative, stories always have "extreme" realizations. Statistics, on the other hand, consist of more than one review and the fraction of positives can therefore also be moderate. For example, when exactly half the observed reviews are positive, the Bayesian belief movement equals zero. Appendix F shows that even for realizations with intermediate extremity, such as 75% positives, Bayesian belief movement is modest. Averaging over all statistics draws lumps together realizations of different extremity and leads to the relatively modest average belief impact seen in our sample. Put simply, all stories are extreme, while statistics are moderate on average.

[23]This difference is smaller than in our baseline experiment possibly because respondents learn that the anecdotal details are not informative beyond the information contained in the quantitative reviews.

[24]Respondents are told that if they choose "don't know", one of the other options will be randomly chosen to determine their payoff.

received was positive or negative.[25] Respondents are told that if they correctly recall the information they received, they will obtain an additional bonus of $5. To avoid hedging, either beliefs or recall were randomly selected for payment, and one question was randomly chosen to determine the bonus. The bottom panel of Appendix Figure A.1 shows that correct recall is significantly higher for stories (69 percent) than for statistics (32 percent).

Willingness to pay To examine whether the information provided in our reviews would likely affect consumer behavior, we elicited a hypothetical willingness to pay measure after the belief elicitation. Table A.2 in Appendix A.1 shows that the *Story* and *Statistic* treatments both significantly increase willingness to pay compared to the no information treatment, both in the *Immediate* and *Delay* conditions. Given that the initial differences in willingness to pay are highly significant, this data does not lend itself to studying memory mechanisms cleanly. Nonetheless, the additional measure suggests that the provided information is related to hypothetical willingness to pay.

3.4.2 Robustness to Other Design Features

In Appendix A, we provide a series of additional robustness analyses. In Appendix A.2, we show that manipulating the valence of story content only has very little effect on accurate recall. In Appendix A.3 we examine the heterogeneity of our findings by positive versus negative information. Appendix A.4 showcases the robustness of the story-statistic gap to different combinations of non-target information. In Appendix A.5, we examine how the size of the story-statistic gap depends on the number of products. Finally, Appendix A.6 confirms the robustness of our findings to using different belief elicitation formats.[26]

3.5 Statistics with Qualitative Content

In line with our conceptualization of stories versus statistics, the story-statistic treatment variation from our baseline experiment changes both the number of reviews and varies

[25]To keep the elicitation for stories and statistics as comparable as possible, we ask respondents who indicated having received multiple reviews whether the majority of reviews was positive or negative, while respondents indicating having received a single review were asked whether the single review was positive or negative. In this elicitation respondents can again select “don’t know”.

[26]In a previous version of this paper we conducted an additional experiment that varied the similarity between different scenario names (Restaurant A, Restaurant B, Restaurant C). This evidence shows that increasing prompt similarity decreases forgetting significantly. Because this design is not tightly connected to the conceptual framework anymore, this evidence is only described in the previous working paper version (Graeber et al., 2022).

the presence of additional qualitative content. In our model of selective memory, however, it is only the latter dimension, qualitative content, that drives the story-statistic gap. To isolate the role of qualitative features, we conduct an additional experiment, in which information-free qualitative features are added to statistics.

Design. The incentives and basic setting closely follow the experiment described in Section 3.4.1. The only difference concerns the information respondents receive: for each product, participants receive either statistical information (condition *Statistic*), statistical information with an uninformative anecdote about one review (condition *Statistic with qualitative content*), or no further information. In the *Statistic with qualitative content* treatment, respondents are told that they receive additional details about one of the reviews. We employ the same reviews as in the baseline experiment and always provide respondents with anecdotal details that are consistent with the direction – more positive or more negative reviews – implied by the statistic.

Sample. We recruited 1000 respondents for the baseline survey. 906 respondents qualified for the follow-up survey. After the pre-specified sample restrictions, our final sample consists of 673 respondents, corresponding to a completion rate of 74 percent.

Results. The top panel of Figure 3 as well as Table A.9 confirm that the decay in belief impact over time is significantly lower for statistics with qualitative content than statistics without qualitative content ($p < 0.01$).[27] The bottom panel of Figure 3 shows that correct recall is significantly higher for statistics with qualitative content than for statistics alone. The average correct recall is 58.10 percent for statistics with qualitative content and 21.40 percent for statistics ($p < 0.01$). These findings confirm our model predictions and underscore the importance of qualitative content in driving the story-statistic gap in memory.

Endogenous qualitative content. In Appendix A.7, we report the design and results of a related experiment. Instead of exogenously adding qualitative content to statistics, we ask respondents to imagine and describe a typical review in light of the statistical information provided. Our results indicate that prompting respondents to come up with a typical review when provided with a statistic increases delayed belief impact and improves recall accuracy, even though immediate updating remains unaffected by the prompt. Put differently, asking participants to add fictional qualitative features to a

[27]Immediate impact for statistics with qualitative content is larger than for statistics without qualitative content, even though all respondents passed an attention screen verifying that they understood that the qualitative information carries no additional information. This possibly arises from the qualitative stimuli enhancing the process of mental simulation (Bordalo et al., 2023a).

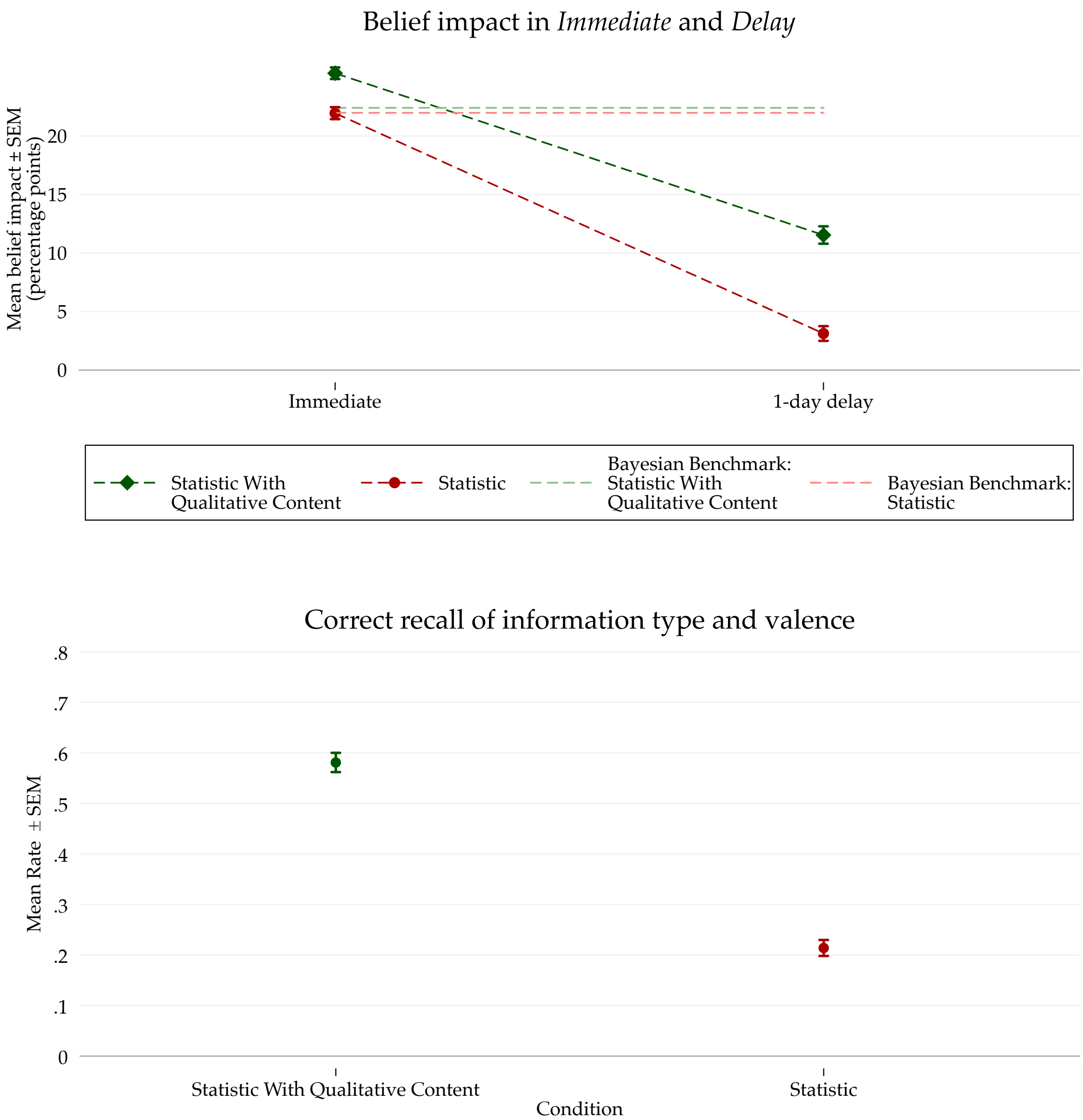


Figure 3: Gap in belief impact and recall for statistics with and without qualitative content (673 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The red markers illustrate belief impact and recall for statistics, while the green markers illustrate belief impact and recall for statistics with qualitative content. The light green markers display the average Bayesian benchmark for statistics with qualitative content (22.41 p.p.), while the light red markers illustrate the average Bayesian benchmark for statistics (21.98 p.p.). Whiskers indicate one standard error of the mean.

statistic on their own decreases the decay in belief impact. This further highlights the crucial role of qualitative content for the story-statistic gap.

3.6 Interpreting the Story-Statistic Gap

There are many differences between stories and statistics that our model abstracts from and may partly account for the story-statistic gap. In the following, we provide a brief overview and discussion.

Engagement with additional information and processing time. Differences in the processing time of stories and statistics, which may be indicative of the encoding strength, are a plausible mechanism underlying the story-statistic gap. We find that respondents spend somewhat more time processing stories (median of 42 seconds) than statistics (median of 32 seconds). Appendix Table A.8 examines heterogeneity in belief impact and recall by the time spent processing the information. Correlationally, we find small and insignificant heterogeneity in differential belief impact based on initial processing time. Moreover, our mechanism experiments in Section 4 hold the processing time of the target scenario constant, as they only vary similarity relationships between the prompt and the qualitative content of stories.

Emotions and vividness. Research in psychology has established a connection between emotions and memory (e.g., Kensinger and Schacter, 2008). Our evidence on the valence of story content (Appendix A.2) suggests that while stories with more consistent qualitative features are recalled at somewhat higher rates than stories with mixed and neutral qualitative story content, these differences are relatively small, especially compared to the large differences in recall between stories and statistics. Moreover, while emotions plausibly play a role in driving the baseline story-statistic gap, the bulk of our mechanism evidence focuses on the features of cue-dependent memory, which allows us to hold emotions fixed.

Outside memories and sample. Respondents do not enter the experiment with a blank slate but bring in an outside database of memories. This existing database contains both stories and statistics to some extent, potentially affecting memory of different types of information. Observing information in the experiment (either in the form of a story or a statistic) might trigger the recall of such outside memories. These recollections from outside the experiment might, in turn, influence beliefs elicited in the experiment. In other words, outside memories might have a *resonance effect*, akin to information resonance in Malmendier and Veldkamp (2022). Our experimental instructions clarify that the only relevant information for the experimental tasks is the one provided within the experiment. Furthermore, it is important to note that such effects, if present, would already influence beliefs in the immediate elicitation. Hence, in order for resonance effects to explain the differences in the dynamic pattern of belief impact between stories and statistics, one would need to allow for such resonance effects to differ between *Immediate* and *Delay*. Alternatively, information resonance might shape how well the information is encoded and stored. Finally, our mechanism experiments, which hold the target information constant and operate by changing the similarity relationships, are immune to the information resonance mechanism.

4 Mechanisms

Guided by the predictions spelled out in Section 2, we proceed with an analysis of underlying mechanisms. First, we investigate the role of cue-target similarity in Section 4.1. Second, we examine interference in Section 4.2.

4.1 Cue-Target Similarity

Our model suggests that one key driving force behind the story-statistic gap is the similarity between the memory cue and the target information. The qualitative content of stories is often related in meaning to the memory cue that originates from the prompt. Therefore, stories more easily come to mind than statistics, which, due to their abstract nature, tend to be unrelated to memory cues. To examine the role of cue-target similarity, we conduct experiments that manipulate the degree of similarity between stories and memory cues arising from the experimental prompt.

Design. The incentives and basic setting closely follow the experiment described in Section 3.4.1. Unlike in the baseline experiments where information types are randomized across scenarios, we here always provide a story in the restaurant scenario. Our key treatment varies, between subjects, the similarity between the story for that scenario and the prompt, i.e., the name of the scenario, which is shown together with the belief elicitation question (both in the *Immediate* and *Delay* condition). Specifically, for the restaurant scenario, each respondent receives either a positive or a negative story. The story describes a reviewer's experience in an Italian restaurant, where the experience makes explicit reference to the Italian cuisine of the restaurant. The scenario identifier, i.e., the label for the restaurant, appears at the top of the belief elicitation page and does not appear in the story itself.[28] In the other two scenarios, respondents receive a statistic and no additional information. We then vary across participants how similar the prompt in the restaurant scenario is to the content of the story. We have three treatment conditions. In the *High Similarity* condition, the name of the restaurant is *The Italian*

[28]Appendix C.2 reproduces the stories.

restaurant "Napoli". In *Low Similarity 1*, the name of the restaurant is *An eatery*, while in *Low Similarity 2* the name of the restaurant is *Mr. Jones*. The high similarity prompt mentions the specific type of Italian cuisine, while the low similarity prompts have no direct association with Italian food. *Low Similarity 1* is a generic term for a dining establishment, while *Low Similarity 2* is a generic name that does not even reveal that the venue of interest is a restaurant.[29] Our design thus varies the experimental prompt, which underlies the memory cue in our model.

Sample. We recruited 1000 respondents for the baseline survey. 912 respondents qualified for the follow-up survey. After the pre-specified sample restrictions, our final sample consists of 627 respondents, corresponding to a completion rate of 69 percent.

Result. Figure 4 and Appendix Table A.10 present the results from this experiment. The upper panel shows results on immediate and delayed belief movement. The figure illustrates that the decay in belief impact over time is significantly lower for *High Similarity* than *Low Similarity 1* ($p < 0.01$) and *Low Similarity 2* ($p < 0.01$). The comparison of belief decay is straightforward as beliefs in *Immediate* do not differ significantly.

The lower panel of Figure 4 confirms these patterns in the recall data. While accurate recall in *High Similarity* is at 80 percent, it is at only 70 percent and 38 percent in *Low Similarity 1* and *Low Similarity 2*, respectively. These effect sizes are large in magnitude and highly statistically significant ($p < 0.01$). Taken together, these results underscore the quantitative importance of the cue-target similarity mechanism.

Reassuringly, Appendix Figure A.11 shows no significant differences in the belief movement and recall for statistics across the three treatments. This suggests that, as intended, our manipulation only affected recall of the restaurant scenario. Moreover, this pattern allows us to cleanly cast our findings in terms of the story-statistic gap. Increasing cue-story similarity significantly increases the story-statistic gap in memory.

Result 2. *Increases in cue-target similarity significantly increase delayed belief impact and recall accuracy.*

[29]We validate these intuitions by computing the cosine-similarity between each of the prompts and the story. Using a tf-idf vectorization with the three prompts and the story as corpus, we obtain a similarity with the story of 0.31 for *The Italian restaurant "Napoli"*, against 0.00 for both *An eatery* and *Mr. Jones*. Using a vectorization based on OpenAI's state-of-the-art embedding model, text-embedding-3-large, we obtain a similarity with the story of 0.52 for *The Italian restaurant "Napoli"*, compared to 0.28 for *An eatery* and 0.10 for *Mr. Jones*.

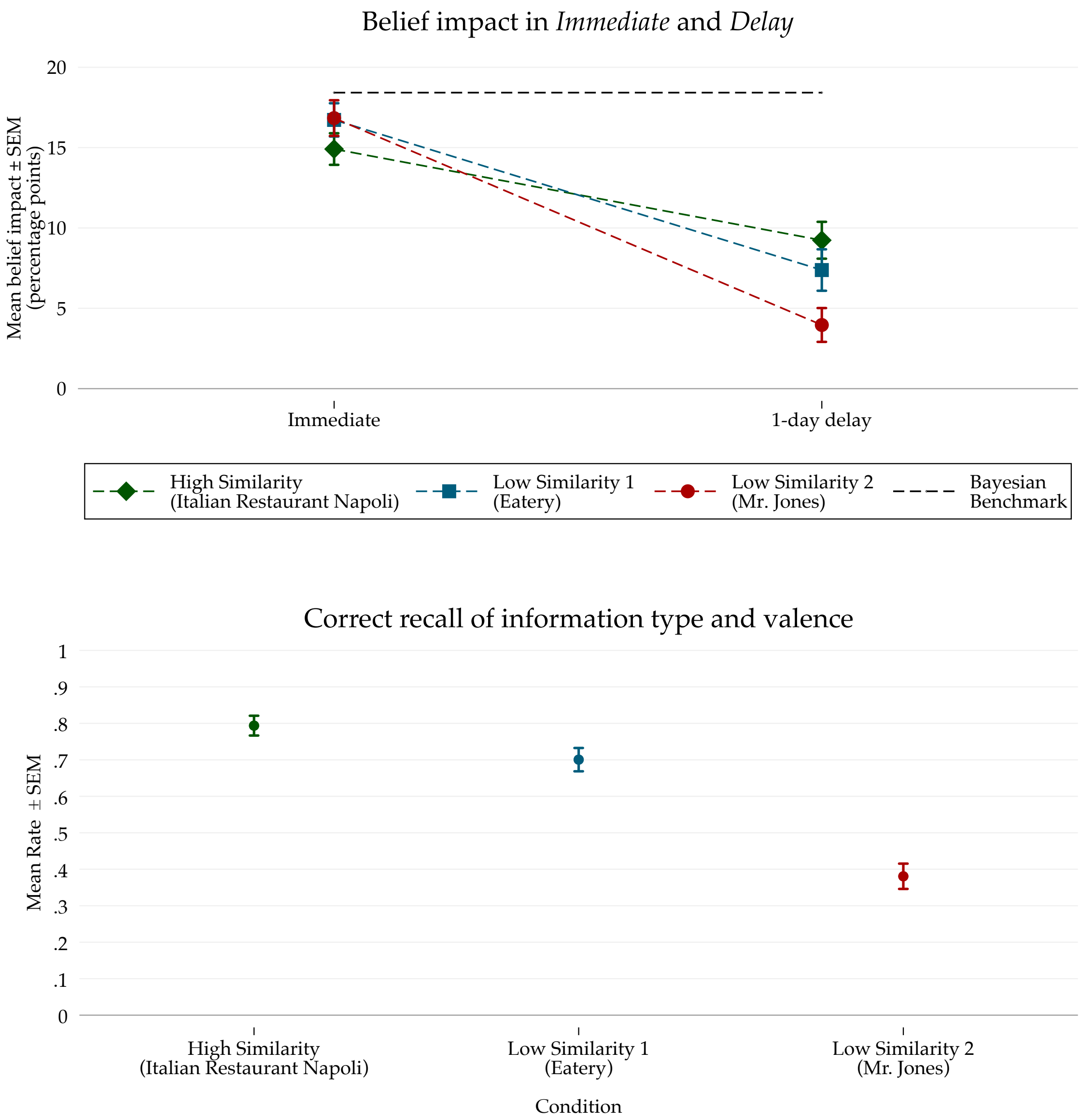


Figure 4: Belief impact and recall in Mechanism Experiment 1 (670 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The green markers illustrate belief impact and recall for *High Similarity*, the blue markers illustrate belief impact and recall for *Low Similarity 1*, while the red markers show belief impact and recall for *Low Similarity 2*. The black markers illustrate the Bayesian benchmark (18.45 p.p.). Whiskers indicate one standard error of the mean.

4.2 Similarity of Cue to Non-Target Information

While the qualitative content of stories tends to give them an edge over statistics due to its natural similarity to the cue, our model also clarifies that qualitative content of non-target information can inhibit the recall of target information due to interference.

Specifically, a direct prediction of our model is that a higher similarity between the memory cue and non-target stories creates memory interference in the recall of target information and hence reduces accurate recall after some delay. To test this prediction, this experiment directly manipulates the similarity between the experimental prompt and a set of non-target stories.

Design. The incentives and basic setting are identical to the mechanism experiment presented in the previous section. We have two treatment conditions that vary, between participants, the similarity of the prompt to non-target information. All participants learn about three scenarios: a food truck, an amusement park, and a sports stadium. Unlike in our main experiment, respondents receive a story in each of the three scenarios. In *Low Interference*, the three stories are distinct and specific to each prompt. Our target story concerns a food truck which describes the quality of a hot dog. Our non-target stories concern a sports stadium and an amusement park, which describe features of the stadium and the amusement park, respectively. In the *High Interference* condition, we keep the target story about the food truck identical to *Low Interference*, but increase the similarity of the two non-target stories to the food truck prompt. In *High Interference*, the two other prompts are still about an amusement park and a sports stadium, but now their corresponding stories describe hot dogs consumed at these locations.[30] Our design thus varies the experimental prompt, which underlies the memory cue in our model.

Thus, our experiment fixes the target story and only manipulates the similarity between the two non-target stories and the food truck prompt.[31] All other design aspects are identical across conditions. Appendix C.3 reproduces all stories that we used.

Sample. We recruited 1,000 respondents, of which 670 qualified for the follow-up.[32] After the pre-specified sample restrictions, we have a sample size of 505, corresponding to a completion rate of 75 percent.[33]

[30]We compute the cosine-similarity between the prompts and the non-target stories across the two treatments with the help of a large-language model. Using a vectorization based on OpenAI's state-of-the-art embedding model, text-embedding-3-large, yields an average similarity of the prompt with the stories in *High Interference* of 0.25 compared to 0.11 in *Low Interference*. This validates our intuitions about the similarity relationships.

[31]The target story concerns a positive review while the non-target stories both feature a negative review.

[32]The somewhat larger fraction of respondents not qualifying for the follow-up study can be explained by them failing our pre-specified inclusion criterion of updating in the right direction in *Immediate* in all three scenarios.

[33]The completion rate to the follow-up survey does not differ significantly across treatment groups ($p = 0.62$).

Results. The top panel of Figure 5 shows data on the belief impact of the target story in *Immediate* and *Delay*, separately for *High Interference* and *Low Interference*. While there is no difference in belief impact in *Immediate*, the slope in belief impact is steeper in *High Interference* compared to *Low Interference*, in line with the model prediction. Delayed belief impact is significantly lower in *High Interference* than in *Low Interference*.

While average delayed belief impact in *High Interference* is 5.91 p.p. (s.e. 1.05), it is 9.86 p.p. (s.e. 1.12) in *Low Interference*. Table A.10 confirms this visual pattern and shows that the difference-in-differences in belief impact (difference in slopes) is statistically significant ($p < 0.01$).[34]

The bottom panel illustrates similar patterns for recall: Among respondents in *Low Interference*, 48.36 p.p. (s.e. 3.43) correctly recall the information, compared to only 31.16 p.p. (s.e. 2.72) in *High Interference*. This difference of 17.2 p.p. is statistically significant ($p < 0.01$). This effect size is moderate in size and corresponds to 0.35 of a standard deviation.[35]

Result 3. *Increases in similarity of the prompt to non-target information significantly decreases delayed belief impact and recall accuracy of the target information.*

Implications. This finding has several implications. First, it provides strong evidence for the power of similarity relationships in determining the decay of belief impact and recall accuracy. Second, it delineates the limits of the stickiness of stories in memory. If the memory database contains many stories that are similar to a cue, retrieval of a target story gets crowded out and it becomes less likely that this story comes to mind. Hence, stories as a communication device lose their edge in environments where similar stories circulate.

5 Decomposing the Story-Statistic Gap

The evidence presented so far leaves some fundamental questions on the processes underlying selective memory unaddressed. One distinction with far-reaching consequences for both theoretical and empirical work is whether distortions induced by memory result from (i) successfully retrieving memories that are subject to partial information loss or

[34]In a previous version of the paper we confirm the robustness of these results on interference using another experiment that featured a different set of prompts and stories but overall employed a similar design (Graeber et al., 2022).

[35]Forgetting in *Low Interference* of this mechanism experiment is higher than in our baseline experiment for potentially two reasons: First, the pieces of additional information (three stories) may be more similar to one another than the information provided in the baseline experiment. Second, respondents in this mechanism experiment receive three pieces of information instead of only two pieces of information in the baseline experiment.

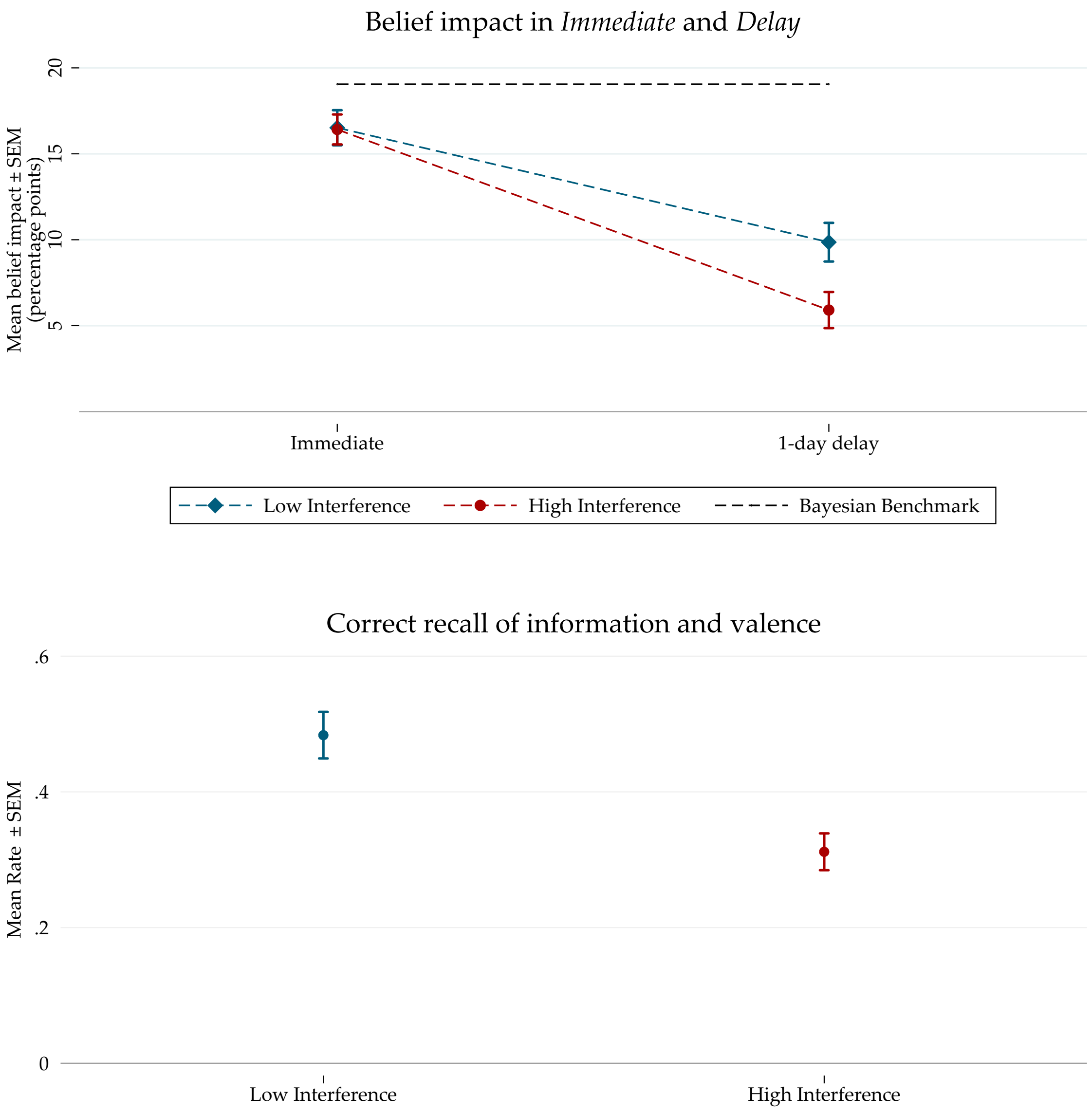


Figure 5: Belief impact and recall in Mechanism Experiment 2 (505 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The blue markers illustrate belief impact and recall for *Low Interference*, while the red markers illustrate belief impact and recall for *High Interference*. Whiskers indicate one standard error of the mean.

(ii) complete retrieval failures. In the following, we provide a decomposition with the purpose of quantifying the importance of these two margins of memory in driving the story-statistic gap.[36]

[36]The analyses in this section are exploratory in nature and were not pre-registered.

Three variants of memory distortions. To examine these ideas, note first that the basic memory retrieval process can have three different possible outcomes: (a) retrieval failure, (b) successful retrieval without information loss, and (c) successful retrieval of a memory trace that is subject to information loss.[37] Each of these retrieval outcomes is associated with a different signature in the decay of belief impact. First, the DM may not retrieve any target memory and beliefs therefore revert to the prior (class *FullDecay*). Second, the DM may correctly recall the full wealth of information contained in a story or statistic (class *ZeroDecay*). In that case, the DM would state their past posterior belief and we would observe no decay in beliefs over time. Third, the DM may successfully recall the target memory trace, but the retrieved information is subject to information loss (class *IntermediateDecay*). The corresponding signature in beliefs would be a partial reversion to the prior.

Empirical approach. The combination of recall data and the evolution of beliefs allow us to shed some light on the relative importance of these margins of memory distortions. We proceed as follows: We use recall data to identify retrieval failures and test whether this class is, in fact, associated with *FullDecay* in the corresponding stated beliefs. We then turn to the remaining data, which, by construction, only include observations where people correctly remember at least some of the information – information type and direction. We focus on the corresponding belief data to assess the relative shares of *ZeroDecay* and *IntermediateDecay*. The following analysis focuses on our baseline experiment reported in Section 3.

Results. First, recall that the bottom panel of Figure 1 identifies the fraction of beliefs associated with retrieval failure, which is defined as incorrect recall of the type and/or direction of the additional information. Following this metric, 38 percent of observations in *Story*, but 71 percent in *Statistic* fail to retrieve relevant information about the target trace. According to the model, these observations should be associated with beliefs that fully revert to the prior of 50%, implying a belief impact of zero (class *FullDecay*). Figure 6 displays the story-statistic gap in belief impact separately for the sample of observations with correct and incorrect recall (following the definition of the bottom panel of Figure 1). The average belief impact for observations classified as *FullDecay* indeed reverts to close to zero in *Delay*, as predicted by the model.

Second, turning to observations with correct recall of type and direction, we can identify the class of *ZeroDecay* as those that state identical beliefs in *Immediate* and *Delay*. This comprises 37.48 percent (46.88 percent of correct recall observations) of all

[37]The latter could be captured by a model that also incorporates noise in the belief formation or retrieval process, along the lines of, e.g., Enke and Graeber (2023); Ba et al. (2023).

observations in *Story* and 27.79 percent (56.05 percent of correct recall observations) of all observations in *Statistic*. Note that these figures likely identify a lower bound, because they do not take into account potential measurement error in beliefs. If people in *ZeroDecay* answer the belief questions with some added random noise, there would be no average belief decay, yet many would state beliefs that differ between the two periods.[38]

Finally, we turn to the remaining class, *IntermediateDecay*, with correct recall of type and direction, but at the same time features beliefs with *some* intensive-margin information loss by virtue of neither being part of *ZeroDecay* nor *FullDecay*. Above we already classified a substantial lower bound for the class *ZeroDecay*. Figure 6 displays average belief decay among observations with correct recall of type and direction. Strikingly, it reveals that there is zero average belief decay in the *Story* condition and a quantitatively minor, only marginally significant decay in the *Statistic* condition. Put differently, conditional on correct recall, we see close to no evidence for belief decay, suggesting a central role of retrieval failures.

Interpretation. Taken together, this exercise provides a clear conclusion: In our experiments, patterns of selective memory are driven by a failure to retrieve any relevant memory for a given scenario, rather than successful recall with partial information loss.

Within-person variation To complement this evidence, we also more systematically examine the within-person movements in beliefs between *Immediate* and *Delay*. To illustrate the connection between second period beliefs, first period beliefs and the ignorance prior, we calculate an individual belief decay parameter, λ, for each participant using the following specification:

$$\text{Belief}_{i2} = \lambda \times \text{IgnorancePrior} + (1 - \lambda) \times \text{Belief}_{i1}$$

where Belief_{i2} is the second-period belief, and where Belief_{i1} is the first-period belief. λ takes value 1 for respondents returning to the ignorance prior, while λ takes value 0 for respondents with perfect recall. Appendix Figure A.12 displays the belief decay estimates for our main experiment. Panel A displays results pooling data from the *Story* and *Statistic* condition, while Panel B displays results for these conditions separately. Panel A highlights that a large fraction of the data is at $\lambda = 1$ and $\lambda = 0$, i.e., full forgetting or full recall. This highlights an all-or-nothing nature of recall in this setting. Panel B shows that there is more mass at $\lambda = 0$ and less mass at $\lambda = 1$ in the *Story*

[38]We can instead apply a more lenient benchmark than precisely zero decay, but, as will be clear below, this will, if anything, only strengthen our conclusion.

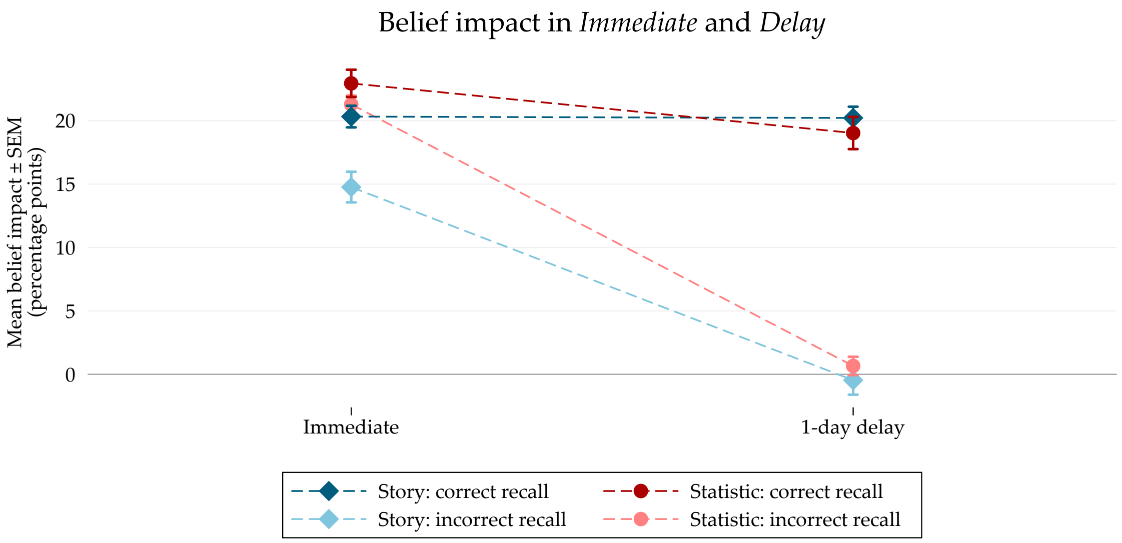


Figure 6: The decay of belief impact by recall accuracy in the baseline experiment (933 respondents). The figure displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The dark blue markers illustrate belief impact for stories with correct recall, while the light blue markers illustrate belief impact for stories with incorrect recall. The dark red markers illustrate belief impact for statistics with correct recall, while the light red markers illustrate belief impact for statistics with incorrect recall. Whiskers indicate one standard error of the mean.

condition compared to the *Statistic* condition. In other words, respondents in the statistic condition are much more likely to state the ignorance prior compared to people in the story condition. Future work should examine the robustness of the all-or-nothing nature of recall in this setting. For example, it is worth exploring whether "partial information loss" becomes more important when there is a longer delay between the receipt and recall of the information.

6 Discussion and Conclusion

This paper documents a story-statistic gap in memory. As time passes, the effect of information on beliefs generally decays, but this decay is much less pronounced for stories than for statistics. Using recall data, we show that stories are more accurately retrieved from memory than statistics. We causally show that this pattern is driven by the presence of qualitative content in stories. Guided by a simple model of cue-dependent memory, we experimentally demonstrate the explanatory power of two key forces of memory: cue-target similarity and interference. Our memory decomposition provides striking evidence that retrieval failures appear to be the key driver of the story-statistic gap, rather than partial information loss in retrieved memories.

Stories in the mass media. Our findings have implications for understanding several real-world phenomena. Mass media provides not only facts and statistics, but also relies on anecdotes about individual cases, which provide detailed qualitative information. Consider allegations about election fraud in the context of the 2020 U.S. presidential election, where some outlets reported stories about individual instances of election fraud, even though these were rare exceptions. Likewise, consider news reporting about welfare fraud where anecdotes about individual cases are abundant in the news media, but stand in stark contrast to official statistics on fraud incidence. For example, Ronald Reagan, beginning with his 1976 campaign, told extreme stories about "welfare queens:"

> *She has 80 names, 30 addresses, 12 Social Security cards and is collecting veterans' benefits on four non-existing deceased husbands. And she's collecting Social Security on her cards. She's got Medicaid, getting food stamps, and she is collecting welfare under each of her names. Her tax-free cash income alone is over $150,000.*

Similar patterns emerge in mass media coverage of immigration. While statistics about low crime rates among immigrants are widely reported by news outlets, extreme stories about immigrants committing severe crimes also regularly hit the headlines. Our results indicate that stories disseminated in this way can have powerful effects on beliefs as they may come to mind more easily than more representative statistical information.

Policy communication. Our results also have implications for the communication of statistical information. If policymakers, marketers or leaders aim to convey statistical information effectively, they may wish to complement it with anecdotes to ensure that the information sticks with the audience. For instance, statistical information about economic quantities could be coupled with anecdotal information that is consistent and inherently reminiscent of the embedded statistical information. Moreover, our results suggest that persuaders should factor in the time structure when picking their mode of persuasion: if messaging occurs close in time to the audience's anticipated action, statistics and quantitative facts can be more powerful than stories; yet, as soon as a delay is involved, stories trump statistics.

Avenues for future research. First, it would be desirable to gain a better understanding of the evolution of memory patterns and the story-statistic gap as time delays increase. Second, to shed light on the external validity of our findings, it will be important to assess whether our results are specific to the recall of statistical information, or whether they instead extend to the recall of simple facts devoid of any context. Third, it would be interesting to understand how memory mechanisms affect the virality of different types of information. Finally, future work might examine whether there is also a gap in the evolution of beliefs between personal and non-personal experiences that is analogous to the story-statistic gap.

References

Afrouzi, Hassan, Spencer Yongwook Kwon, Augustin Landier, Yueran Ma, and David Thesmar, "Overreaction in Expectations: Evidence and Theory," *Quarterly Journal of Economics*, 2023, *138* (3), 1713–1764.

Alesina, Alberto, Armando Miano, and Stefanie Stantcheva, "Immigration and Redistribution," *Review of Economic Studies*, 2023, *90* (1), 1–39.

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart, "Subjective Models of the Macroeconomy: Evidence from Experts and Representative Samples," *Review of Economic Studies*, 2022, *89* (6), 2958–2991.

_ , Ingar Haaland, Christopher Roth, and Johannes Wohlfart, "Narratives about the Macroeconomy," *Working Paper*, 2022.

Ba, Cuimin, Aislinn Bohren, and Alex Imas, "Over- and Underreaction to Information," *Working Paper*, 2023.

Baddeley, Alan, Michael W. Eysenck, and Michael C. Anderson, *Memory*, Routledge, 2020.

Barron, Kai and Tilman Fries, "Narrative persuasion," 2023.

Bénabou, Roland, Armin Falk, and Jean Tirole, "Narratives, Imperatives, and Moral Reasoning," *Working Paper*, 2018.

Bordalo, Pedro, Giovanni Burro, Katie Coffman, Nicola Gennaioli, and Andrei Shleifer, "Imagining the Future: Memory, Simulation and Beliefs," *Review of Economic Studies*, 2023.

_ , John J Conlon, Nicola Gennaioli, Spencer Y Kwon, and Andrei Shleifer, "How People Use Statistics," *Working Paper*, 2023.

_ , _ , _ , _ , and _ , "Memory and Probability," *Quarterly Journal of Economics*, 2023, *138* (1), 265–311.

_ , Katherine Coffman, Nicola Gennaioli, Frederik Schwerter, and Andrei Shleifer, "Memory and Representativeness.," *Psychological Review*, 2021, *128* (1), 71.

_ , Nicola Gennaioli, and Andrei Shleifer, "Memory, Attention, and Choice," *Quarterly Journal of Economics*, 2020, *135* (3), 1399–1442.

_ , _ , Yueran Ma, and Andrei Shleifer, "Overreaction in macroeconomic expectations," *American Economic Review*, 2020, *110* (9), 2748–82.

Bower, Gordon H and Michal C Clark, "Narrative stories as mediators for serial learning," *Psychonomic Science*, 1969, *14* (4), 181–182.

Brewer, William F and James C Treyens, "Role of schemata in memory for places," *Cognitive Psychology*, 1981, *13* (2), 207–230.

Bruner, Jerome, "Actual Minds, Possible Worlds (Jerusalem-Harvard Lectures)," 1987.

Bursztyn, Leonardo, Aakaash Rao, Christopher P Roth, and David H Yanagizawa-Drott, "Opinions as Facts," *Review of Economic Studies*, 2023, *90* (4), 1832–1864.

_ **, Georgy Egorov, Ingar Haaland, Aakaash Rao, and Christopher Roth**, "Justifying dissent," *The Quarterly Journal of Economics*, 2023, *138* (3), 1403–1451.

Charles, Constantin, "Memory and Trading," *Working Paper*, 2022.

Conlon, John J and Dev Patel, "What Jobs Come to Mind? Stereotypes about Fields of Study," *Working Paper*, 2022.

Danz, David, Lise Vesterlund, and Alistair Wilson, "Belief Elicitation and Behavioral Incentive Compatibility," *American Economic Review*, 2022, *112* (9), 2851–2883.

Eliaz, Kfir and Ran Spiegler, "A Model of Competing Narratives," *American Economic Review*, 2020, *110* (12), 3786–3816.

Enke, Benjamin, "What You See Is All There Is," *Quarterly Journal of Economics*, 2020, *135* (3), 1363–1398.

_ **and Florian Zimmermann**, "Correlation Neglect in Belief Formation," *Review of Economic Studies*, 2019, *86* (1), 313–332.

_ **and Thomas Graeber**, "Cognitive uncertainty," *The Quarterly Journal of Economics*, 2023, *138* (4), 2021–2067.

_ **, Frederik Schwerter, and Florian Zimmermann**, "Associative Memory, Beliefs and Market Interactions," *Journal of Financial Economics*, 2023.

Foer, Joshua, *Moonwalking with Einstein: The Art and Science of Remembering Everything*, Penguin, 2012.

Fryer, Bronwyn, "Storytelling That Moves People," *Harvard Business Review*, 2003.

Gennaioli, Nicola and Andrei Shleifer, "What Comes to Mind," *Quarterly Journal of Economics*, 2010, *125* (4), 1399–1433.

Graeber, Thomas, "Inattentive inference," *Journal of the European Economic Association*, 2023, *21* (2), 560–592.

__ , **Christopher Roth, and Constantin Schesch**, "Explanations," 2024.

__ , **Florian Zimmermann, and Christopher Roth**, "Stories, statistics, and memory," 2022.

__ , **Shakked Noy, and Christopher Roth**, "Lost in Transmission," 2024.

Hartzmark, Samuel, Samuel Hirshman, and Alex Imas, "Ownership, Learning, and Beliefs," *Quarterly Journal of Economics*, 2021, *136* (3), 1665–1717.

Heath, Chip and Dan Heath, *Made to Stick: Why Some Ideas Survive and Others Die*, Random House, 2007.

Hossain, Tanjim and Ryo Okui, "The Binarized Scoring Rule," *Review of Economic Studies*, 2013, *80* (3), 984–1001.

Jiang, Zhengyang, Hongqi Liu, Cameron Peng, and Hongjun Yan, "Investor Memory and Biased Beliefs: Evidence from the Field," *Working Paper*, 2022.

Kahana, Michael Jacob, *Foundations of Human Memory*, OUP USA, 2012.

Kendall, Chad W and Constantin Charles, "Causal Narratives," *Working Paper*, 2022.

Kensinger, Elizabeth A and Daniel L Schacter, "Memory and Emotion," 2008.

Kwon, Spencer Yongwook and Johnny Tang, "Extreme Events and Overreaction to News," *Working Paper*, 2023.

Link, Sebastian, Andreas Peichl, Christopher Roth, and Johannes Wohlfart, "Attention to the Macroeconomy," *Working Paper*, 2023.

Malmendier, Ulrike and Laura Veldkamp, "Information resonance," Technical Report, Working Paper 2022.

__ **and Stefan Nagel**, "Depression babies: Do macroeconomic experiences affect risk taking?," *The quarterly journal of economics*, 2011, *126* (1), 373–416.

__ **and** __ , "Learning from inflation experiences," *The Quarterly Journal of Economics*, 2016, *131* (1), 53–87.

Mandler, Jean M., *Stories, Scripts, and Scenes: Aspects of Schema Theory*, Erlbaum, 1984.

Martínez-Marquina, Alejandro, Muriel Niederle, and Emanuel Vespa, "Failures in Contingent Reasoning: The Role of Uncertainty," *American Economic Review*, 2019, *109* (10), 3437–74.

McAdams, Dan P, "Narrative Identity," *Handbook of Identity Theory and Research*, 2011, pp. 99–115.

McRae, Ken and Michael Jones, *14 Semantic Memory*, Vol. 206, Oxford University Press Oxford, 2013.

Michalopoulos, Stelios and Melanie Meng Xue, "Folklore," *Quarterly Journal of Economics*, 2021, *136* (4), 1993–2046.

Monarth, Harrison, "The Irresistible Power of Storytelling as a Strategic Business Tool," *Harvard Business Review*, 2014.

Morag, Dor and George Loewenstein, "Narratives and Valuations," *Working Paper*, 2021.

Peer, Eyal, David Rothschild, Andrew Gordon, Zak Evernden, and Ekaterina Damer, "Data quality of platforms and panels for online behavioral research," *Behavior Research Methods*, 2022, *54* (4), 1643–1662.

Schacter, Daniel L, *Searching for Memory: The Brain, The Mind, And The Past*, Basic books, 2008.

Schank, Roger C. and Robert P. Abelson, *Scripts, plans, goals, and understanding: An inquiry into human knowledge structures*, Erlbaum, 1977.

Shepard, Roger N, "Recognition memory for words, sentences, and pictures," *Journal of verbal Learning and verbal Behavior*, 1967, *6* (1), 156–163.

— **and Lynn A Cooper**, *Mental images and their transformations.*, The MIT Press, 1986.

Shiller, Robert J, "Narrative Economics," *American Economic Review*, 2017, *107* (4), 967–1004.

— , *Narrative Economics*, Princeton University Press, 2020.

Standing, Lionel, "Learning 10000 pictures," *Quarterly Journal of Experimental Psychology*, 1973, *25* (2), 207–222.

Online Appendix: Stories, Statistics, and Memory

Thomas Graeber Christopher Roth Florian Zimmermann

Summary of the Online Appendix

Section A provides an overview of various additional robustness experiments. Section B displays additional tables and figures. Section C provides an overview of the different stories we used in the experiments. Section D illustrates details on the implementation of the randomization. Appendix E provides details on our hand-coding scheme. Appendix F explains how one can compute the Bayesian benchmarks for our setting and gives intuitions. Finally, Appendix G provides proofs for our theoretical results.

A Robustness: Additional Results

A.1 Uninformative Stories

Uninformative qualitative content. The design is identical to our baseline except that we explicitly tell respondents that the anecdotal details do not carry any information above and beyond the number of positive reviews among the collection of randomly drawn reviews. In particular, they receive the following prompt:

> There is a possibility that you will also receive additional anecdotal details about a reviewer and their experience with the product. Note that these additional, anecdotal details do not carry any information above and beyond the number of positive reviews among the collection of randomly drawn reviews. In other words, what matters for your guess is the number of positive reviews among the collection of randomly drawn reviews.

To ensure that our respondents actually internalize this information they need to pass the following comprehension check:

> Which of the following two statements is true?
>
> - What matters for my guess is the number of positive reviews among the collection of randomly drawn reviews.
> - What matters for my guess are only the anecdotal details about the reviewer and their experience with the product cannot help me make a better guess.

Willingness to pay elicitation. We also elicit a hypothetical willingness to pay for each product after the respective belief elicitation, both in the initial and follow-up survey. Respondents are provided with the typical price of the respective products with average reviews as an anchor. For example, in the case of the bicycle they receive the following instructions:

> Assuming you were in need of a bicycle, how much would you be willing to pay for this bike?
>
> To provide a reference, the typical price of a bicycle with average reviews is $600.

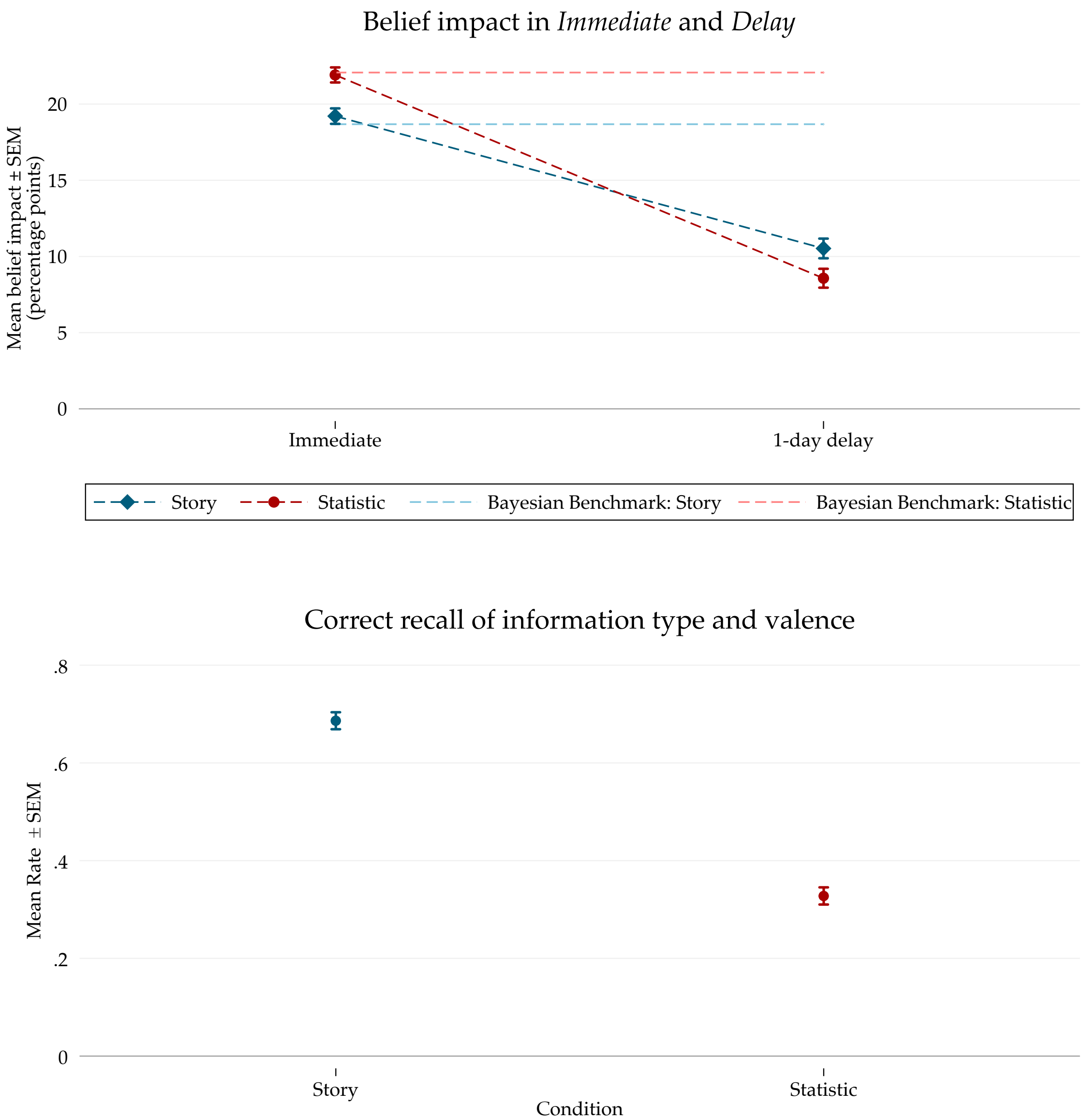


Figure A.1: The story-statistic gap in Robustness experiment 1: Uninformative Qualitative Content (714 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The red markers illustrate belief impact and recall for statistics, while the blue markers illustrate belief impact and recall for stories. The light blue markers illustrate the average Bayesian benchmark for stories (18.70 p.p.), while the light red markers displays the average Bayesian benchmark for statistics (22.07 p.p.). Whiskers indicate one standard error of the mean.

Table A.1: The story-statistics gap in memory — uninformative stories

	Dependent variable:			
	Belief Impact			Correct Recall
Sample:	Immediate (1)	Delay (2)	Pooled (3)	Pooled (4)
Story	-2.70***	1.96*	-2.70***	0.36***
	(0.90)	(1.15)	(0.74)	(0.02)
Delay			-13.3***	
			(0.78)	
Story × Delay			4.66***	
			(0.99)	
Control Mean	21.91	8.57	21.91	0.33
Observations	1428	1428	2856	1428
R^2	0.60	0.59	0.47	0.13

Notes. This Table uses responses from the *Story* and *Statistic* condition in Robustness experiment 1. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Story* takes value 1 for respondents who received a story for a given product, and zero otherwise. *Statistic* takes value 1 for respondents who received a statistic for a given product, and zero otherwise. All columns include respondents who received consistent stories. Column (3) pools *Immediate* and *Delay*. All columns display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Impact on willingness to pay

	Dependent variable: Standardized WTP Impact	
Sample:	Story vs. No Info (1)	Statistic vs. No Info (2)
Constant	-0.53***	-0.53***
	(0.04)	(0.04)
Story	0.81***	
	(0.05)	
Statistic		0.73***
		(0.05)
Delay	-0.07**	-0.07**
	(0.03)	(0.03)
Story × Delay	0.11***	
	(0.03)	
Statistic × Delay		0.09**
		(0.04)
Observations	2766	2816
R^2	0.18	0.15

Notes. Column (1) of this table uses responses from the *Story* and *No Information* conditions, while column (2) uses the *Statistic* and *No Information* conditions. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Story* takes value 1 for respondents who received a story for a given product, and zero otherwise. *Statistic* takes value 1 for respondents who received a statistic for a given product, and zero otherwise. All columns include respondents who received consistent stories. All columns display results on standardized WTP impact. Standardized WTP impact is the absolute distance between the stated WTP and the provided anchor, winsorized at 1st and 99th percentile and standardized separately for the six categories (Bicycle, Restaurant, Video game) × (*Immediate*, *Delay*). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Valence of Story Content

To examine the importance of the valence of the story content, our baseline experiment cross-randomized whether the qualitative information in the stories was (i) consistently positive or negative in line with the review rating, (ii) of mixed valence, or (iii) neutral (see Appendix C for all stories). Mixed valence stories mention both positive and negative aspects of the scenario. Neutral valence stories, on the other hand, do not contain evaluations, but describe the experience in the scenario without judgment.

Figure A.2 shows that the valence of story content has minor but significant effects.[1] Average correct recall is 61.61 percent in the consistent story condition compared to 59.46 and 50.50 percent in the mixed and neutral stories treatments, respectively. These levels of recall are substantially higher compared to 28.40 percent for statistics, indicating that the story-statistic gap is robust to variations in the valence of the story content. The patterns for belief impact are consistent with the recall evidence. While belief impact in *Immediate* does indeed depend on the valence of the qualitative information, these differences are strongly attenuated in *Delay*.

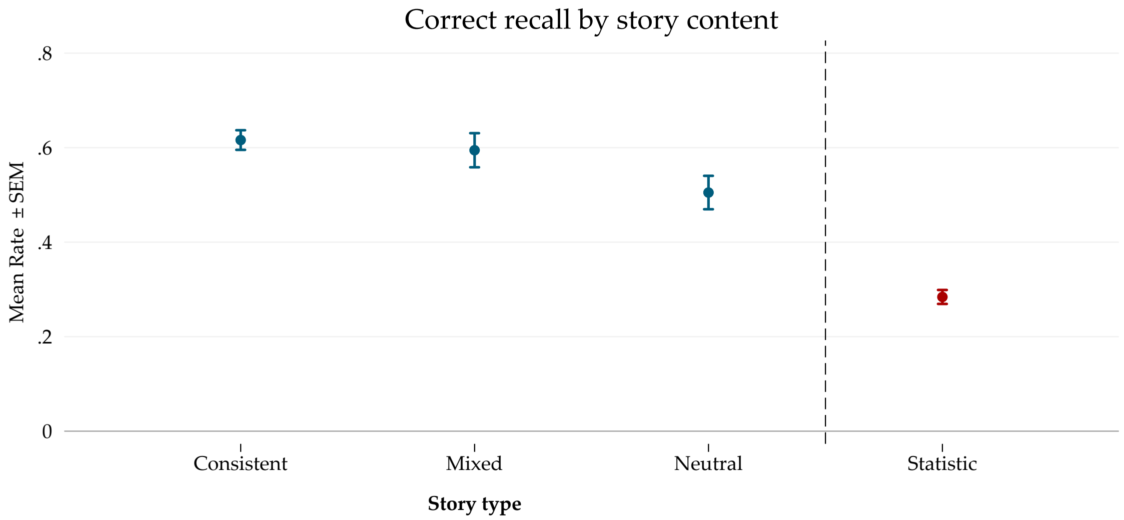


Figure A.2: Correct recall of type and direction by story type in the baseline experiment (933 respondents). The figure shows the fraction of correct recall of the type and direction of information received in the baseline survey in *Delay* for respondents in the *Story* condition (blue) and *Statistic* condition (red). Consistent refers to stories with qualitative features whose direction was fully consistent with the direction of the review. Mixed refers to stories with qualitative features whose direction is mixed. Neutral refers to stories with qualitative features whose direction is neutral. Whiskers indicate one standard error of the mean.

[1]Since we expected the valence manipulation to have potentially strong effects on immediate updating, we pre-registered using recall performance as our main outcome measure.

A.3 Heterogeneity by Positive Versus Negative Reviews

We test for potential heterogeneity in belief impact and correct recall between positive and negative reviews. Figure 2 in the main text already illustrates that there is a pronounced story-statistic gap for both positive and negative reviews. In fact, we find no difference in recall performance, whether the reviews are positive or negative (*Story*: $p = 0.844$, *Statistic*: $p = 0.380$). Moreover, there is no heterogeneity in the evolution of belief impact for *Story* by the direction of the quantitative information ($p = 0.874$) . However, we observe that positive statistics affect beliefs more persistently than negative statistics ($p = 0.0012$).

A.4 Robustness to Different Non-Target Information

We exogenously manipulate the type of information for the two non-target scenarios. Respondents either received two statistics for the non-target scenarios, two stories or twice no information. In addition, in contrast to the baseline design, we fully randomize the direction of the information provided for each scenario. In the follow-up survey, we elicit beliefs exactly as in the baseline experiment, presented in Section 3.1.

Sample. We recruited 2,250 respondents for the baseline survey. 2048 respondents qualified for the follow-up survey. 1,613 respondents completed the one-day follow-up survey. After the pre-specified sample restrictions, our final sample consists of 1,548 respondents, corresponding to a 76% completion rate.[2]

Results. Figure A.3 summarizes our results. The left-hand panel shows the changes in belief impact between immediate and delay for the target story and target statistic across the three different conditions. The right panel analogously displays the rate of correct recall across the three conditions separately for the story and statistic target.

We make three observations: First, there is a robust story-statistic gap across all conditions. The story-statistic gap has a similar magnitude irrespective of the number and type of non-target information. This is visible across both our beliefs data and the incentivized structured recall elicitation.[3] Second, we observe small effects at best of the number of decoy information. This suggests that memory load per se has muted effects on belief impact in this setting. Third, we do not observe significant effects of the type of decoy information on the size of the story-statistic gap. Jointly these results imply that the story-statistic gap is robust to basic features of the decoys and that – in a setting with only three scenarios – the type and number of decoys is not a key driver of the decay of belief impact.

Figure A.4 shows how belief impact and recall of stories vary depending on the direction of decoy information. Compared to the statistics benchmark, we again find a robust and sizable story-statistic gap across decoys of different direction. We further find that decoy direction has a small but directionally plausible effect on the size of the gap: when decoy information has the same direction as the target information, both recall and delayed belief impact is larger than when the decoy information is mixed or of opposite sign.

[2]The completion rate to the follow-up survey does not differ significantly across treatment groups ($p = 0.60$).

[3]Results from our structured recall task are very similar to results from the free recall task, providing a validation of the latter.

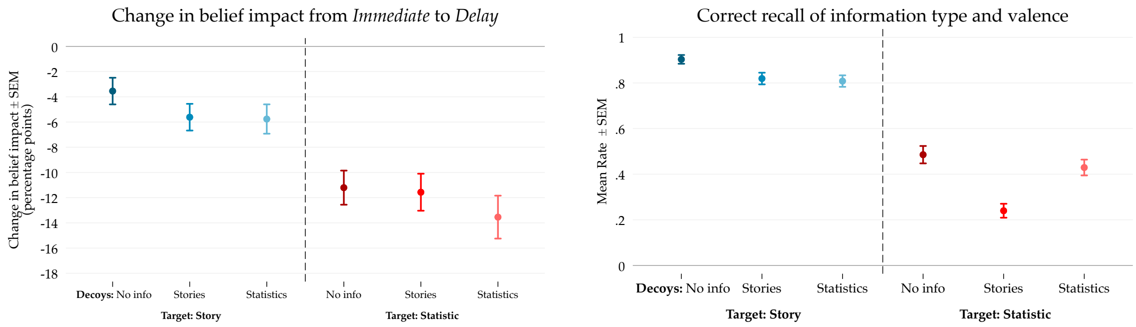


Figure A.3: Belief impact and recall in Robustness Experiment 2: The role of Decoy Information (1,513 respondents). The left panel displays the change in belief impact in percentage points, defined as the difference in belief impact between *Delay* and *Immediate*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The dark blue (dark red) markers illustrate change in belief impact and recall for stories (statistics) for the *Decoys: No Info* condition, the blue (red) markers illustrate the change in belief impact and recall for stories (statistics) for the *Decoys: Stories* condition, while the light blue (light red) markers display the change in belief impact and recall for stories (statistics) for the *Decoys: Statistics* condition. Whiskers indicate one standard error of the mean.

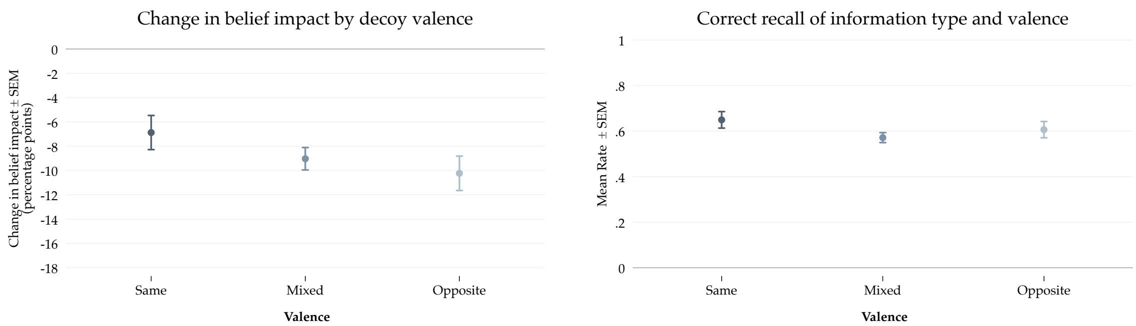


Figure A.4: Belief impact and recall in Robustness Experiment 2: The role of Decoy Information (1,513 respondents). The top panel displays the change in belief impact in percentage points, defined as the difference in belief impact between *Delay* and *Immediate*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The right panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The dark gray markers illustrate change in belief impact and recall for targets when decoys have the target's direction, the gray markers illustrate change in belief impact and recall for targets when decoys have mixed direction, while the light gray markers display the change in belief impact and recall for targets when decoys have the target's opposite direction. Whiskers indicate one standard error of the mean.

A.5 The Number of Product Scenarios

In this section we examine the robustness of our findings to varying the number of products. We examine how the size of the story-statistic gap varies depending on whether there are one, three or six products.

Design. The design broadly follows the structure of the main experiment. The key difference is that we vary, between subjects, whether there are one, three or six product scenarios. In the *1-product* treatment, there is a single scenario and participants only received one piece of information, either a story or a statistic. Identical to the baseline experiment, participants in the *3-product* treatment see three scenarios and receive two pieces of information, one story, one statistic and once no information. In the *6-product* treatment, participants see six scenarios overall and also receive two pieces of information (one story and one statistic), as well as four times no information. This means that the comparison between the *3-product* and *6-product* design allows us to cleanly study the effects of the number of product scenarios, while holding the total pieces of information constant; in other words respondents in both the *6-product* and *3-product* treatments receive one statistic and one story.[4]

To keep incentives exactly constant between the different conditions, participants in all treatments complete a total of six payoff-relevant tasks in both *Immediate* and *Delay*: the additional filler tasks are incentivized dot estimation tasks. Respondents in the 1-product treatment arm complete 5 dot estimation tasks, while respondents in the 3-product treatment arm complete 3 dot estimation tasks, and respondents in the 6-product treatment only face product-related tasks.

Sample. We recruited 1500 respondents. 1404 respondents qualified for the follow-up survey. After the pre-specified sample restrictions, our final sample consists of 1018 respondents, corresponding to a completion rate of 73 percent.[5]

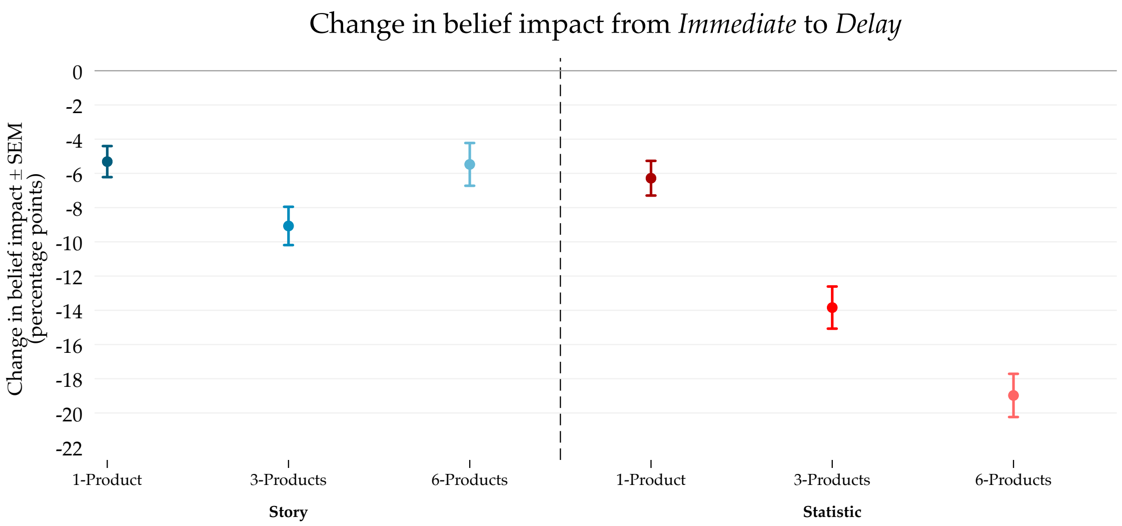
Results. Figure A.5 and Table A.3 illustrate changes in belief impact between *Immediate* and *Delay* as well as recall for stories and statistics across the different number of product scenarios. The top panel depicts the change in belief impact between *Immediate* and *Delay* across the three treatment arms, separately for stories and statistics. We find that, overall, the change in belief impact tends to become more pronounced as we increase the number of product scenarios. This effect is relatively small for stories. In fact, the *6-product* treatment does not lead to a more pronounced decay of belief impact than the *3-product* and *1-product* versions. At the same time, the effect of more scenarios on the decay of belief impact is quantitatively large for statistics. As a consequence, and in line with our model, the story-statistic gap widens with the number of product scenarios.[6]

[4]The comparison between the *1-product* and *3-product* condition jointly identifies the effects of increasing the total number of products and increasing the pieces of information.

[5]The completion rate to the follow-up survey does not differ significantly across treatment groups ($p = 0.37$).

[6]The story-statistic gap in belief impact is close to zero for the 1-product scenario.

This pattern is strongly supported by the recall data, see the bottom panel of Figure A.5. Recall accuracy of statistics drastically decreases as we move from 1 to 3 to 6 scenarios, while recall accuracy of stories remains comparably stable.



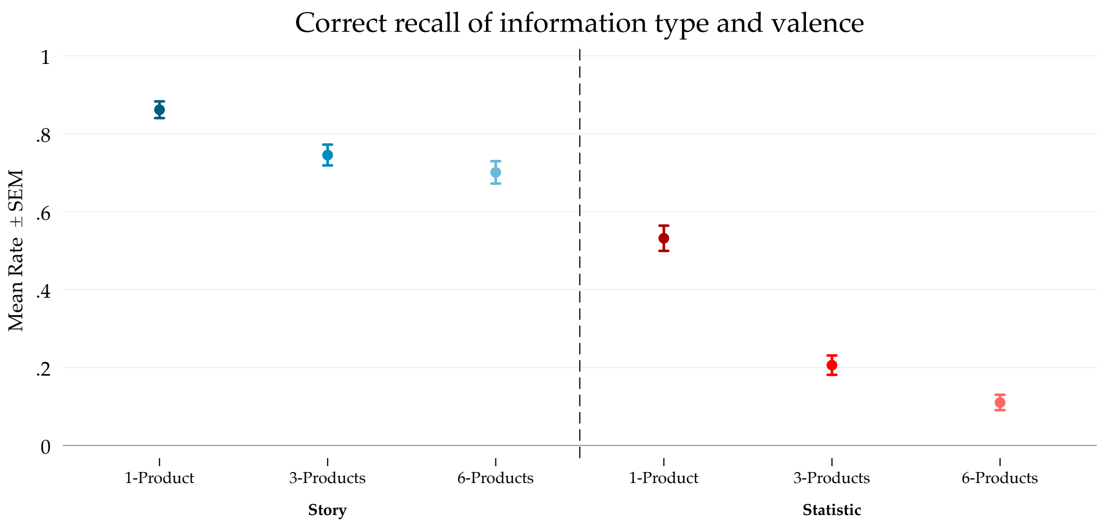


Figure A.5: Change in belief impact and recall in Robustness Experiment 3: Number of product scenarios (1,018 respondents). The top panel displays the change in belief impact in percentage points, defined as the difference in belief impact between *Delay* and *Immediate*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The dark blue markers illustrate change in belief impact and recall for the *1-product* condition, the blue markers illustrate the change in belief impact and recall for the *3-product* condition, while the light blue markers display the change in belief impact and recall for the *6-product* condition. Whiskers indicate one standard error of the mean.

Table A.3: The story-statistic gap by number of products

	Dependent variable:			
	Belief Impact		Combined Recall	
Sample:	Story	Stat	Story	Stat
	(1)	(2)	(3)	(4)
1-Product	-1.02	2.26	0.12***	0.33***
	(1.39)	(1.44)	(0.03)	(0.04)
Delay × 1-Product	3.76***	7.52***		
	(1.44)	(1.59)		
6-Products	-1.44	2.76**	-0.045	-0.096***
	(1.49)	(1.38)	(0.04)	(0.03)
Delay × 6-Products	3.60**	-5.13***		
	(1.68)	(1.76)		
Delay	-9.07***	-13.8***		
	(1.12)	(1.23)		
Control Mean	18.48	18.51	0.75	0.21
Observations	1562	1515	781	758
R^2	0.04	0.19	0.03	0.16

Notes. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *1-Product* is an indicator taking value 1 if the respondent receives one product scenario and 0 else. *6-Products* is an indicator taking value 1 if the respondent receives six product scenarios and 0 else. Columns (1) and (3) include respondents who received stories, while column (2) and (4) include respondents who received statistics. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Columns (3) and (4) display the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.6 Robustness to Elicitation Format

It is conceivable that the question format of the belief elicitation affects the story-statistic gap, because the specific wording of the question might favor the recall of stories over statistics. In an additional experiment, we independently manipulated the question format as well as the display format of the statistic.

Design. First, the *Likelihood Format* treatment elicited beliefs as before – about the likelihood that a randomly chosen review is positive – and thus exactly corresponded to our main experiment. In the *Fraction Format* condition, by contrast, we elicited beliefs about the percentage of positive reviews in the overall population of reviews of the product. Second, we randomized whether the statistical information itself was expressed in terms of an absolute number of positive reviews in a subsample – as in our main study – (*Statistic Number Display*) or in terms of a percentage of positive reviews in a subsample (*Statistic Percent Display*).

Sample. We recruited 1500 respondents. 1400 respondents qualified for the follow-up survey. After the pre-specified sample restrictions, our final sample consists of 818 respondents, corresponding to a completion rate of 58 percent.[7,8]

Results. Figure A.6 shows that the fraction question format has a positive, albeit small effect on delayed belief impact and recall. Moreover, displaying statistical information as a percentage instead of an absolute number does not have significant effects on belief impact and recall. We also do not observe a significant interaction effect between the question format and the display format of statistical information. Taken together, this evidence highlights that the story-statistic gap in memory is robust to the exact question format used.

Given that the way the statistical information is presented should affect the computational complexity of calculating immediate beliefs, our evidence provides suggestive evidence that computational complexity and the associated cognitive load do not seem to play a quantitatively important role.

[7]We exclude observations of 141 participants in Robustness Experiment 4 who were affected by a technical error in the survey code in wave 1. When the drawn statistic corresponded to a share of 100% positive reviews, no numbers were displayed on the screen. Including these additional participants leaves virtually all results unchanged.

[8]The completion rate to the follow-up survey does not differ significantly across treatment groups ($p = 0.67$).

Table A.4: Question format: belief impact and recall

	Dependent variable:			
	Belief Impact		Combined Recall	
Sample:	Story (1)	Stat (2)	Story (3)	Stat (4)
Similar Format	2.31^{**} (1.14)	0.48 (1.23)	0.010 (0.03)	0.090^{**} (0.04)
Delay × Similar Format	-0.82 (1.36)	1.79 (1.95)		
Statistic Similar		0.27 (1.28)		0.0057 (0.04)
Delay × Statistic Similar		0.62 (1.88)		
Statistic Similar × Similar Format		-2.16 (1.76)		-0.076 (0.06)
Delay × Statistic Similar × Similar Format		-0.87 (2.67)		
Delay	-8.13^{***} (0.90)	-15.6^{***} (1.37)		
Control Mean	18.32	21.89	0.73	0.20
Observations	1632	1631	818	818
R^2	0.06	0.20	0.00	0.01

Notes. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Similar Format* takes value 1 for respondents whose beliefs were elicited in percent. *Statistic Similar* is an indicator taking value 1 for respondents who received statistics in a percentage format. Columns (1) and (3) include respondents who received stories. Columns (2) and (4) include respondents who received statistics. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Columns (3) and (4) display the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

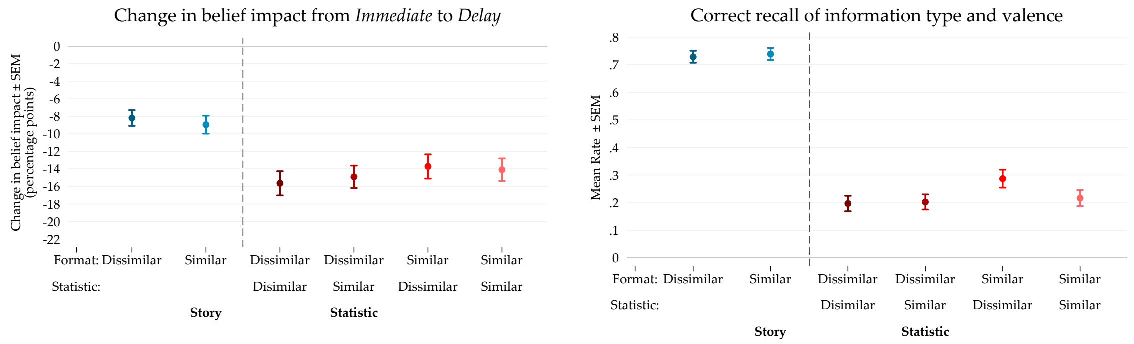


Figure A.6: Belief impact and recall in Robustness Experiment 4: Question Format and statistic display (818 respondents). The left panel displays the change in belief impact in percentage points, defined as the difference in belief impact between *Delay* and *Immediate*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The right panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The dark blue markers illustrate change in belief impact and recall for the *Dissimilar Format* condition for stories, the light blue markers illustrate change in belief impact and recall for the *Similar Format* condition for stories, while the most dark red for the *Dissimilar Format / Statistic Dissimilar* condition, the dark red for the *Dissimilar Format / Statistic Similar* condition, the red for the *Similar Format / Statistic Dissimilar* condition and the light red for the *Similar Format / Statistic Similar* condition. Whiskers indicate one standard error of the mean.

A.7 The Role of Qualitative Associations

Design. To causally examine the role of adding qualitative features *while holding the amount of information content provided constant*, we prompt respondents to imagine a typical review for the statistic or for a single review they learn about. This treatment does not provide any objective information, qualitative or quantitative, allowing us to identify the distinct effect of associating obviously fictional qualitative features with a piece of information in memory.

We implement four conditions. In *Baseline*, we replicate our main design. The *StatisticPrompt* condition is identical to *Baseline*, except that respondents that receive the statistic are prompted "to imagine how a typical review based on the provided information would look like."

To examine the role of associations for single reviews that do not contain any qualitative features, we design two additional treatments. The *NoStory* condition is identical to *Baseline*, except that instead of a story, respondents receive information about a single review without any qualitative information. The *NoStoryPrompt* condition is identical to *NoStory* except that respondents that received information about a single review are asked to imagine what the review might look like, similar to *StatisticPrompt*. The rationale behind these two conditions is to examine what happens when the story provided in the *Story* condition of our main experiment is stripped of its actual content and then replaced by an endogenously generated one. The prompt in turn may push people to retrieve personal experiences that they have made with similar products in the past.

We use a structured recall task. We ask respondents to indicate whether they (i) received information about a single review, including some additional anecdotal details about the reviewer and their experience with the product, (ii) multiple reviews, (iii) no information or (iv) don't know. Unless respondents indicate that they did not receive any information about this product, we additionally ask them to indicate whether the information they received was positive or negative. Respondents are told that if they correctly recall the information they received, they will receive an additional bonus of $5. To circumvent hedging motives, either beliefs or recall were randomly selected for payment, and one question was randomly chosen to determine the bonus.

Sample and pre-registration. 1,500 respondents completed wave 1 of our experiment, with 1,442 qualifying for wave 2. Of those, 703 respondents actually completed wave 2. 666 of the final set of respondents satisfied our inclusion criteria, corresponding to a completion rate of 46 percent.[9]

Prediction. The decay of belief impact and forgetting is lower in the *Prompt* conditions than in the *No Prompt* conditions.

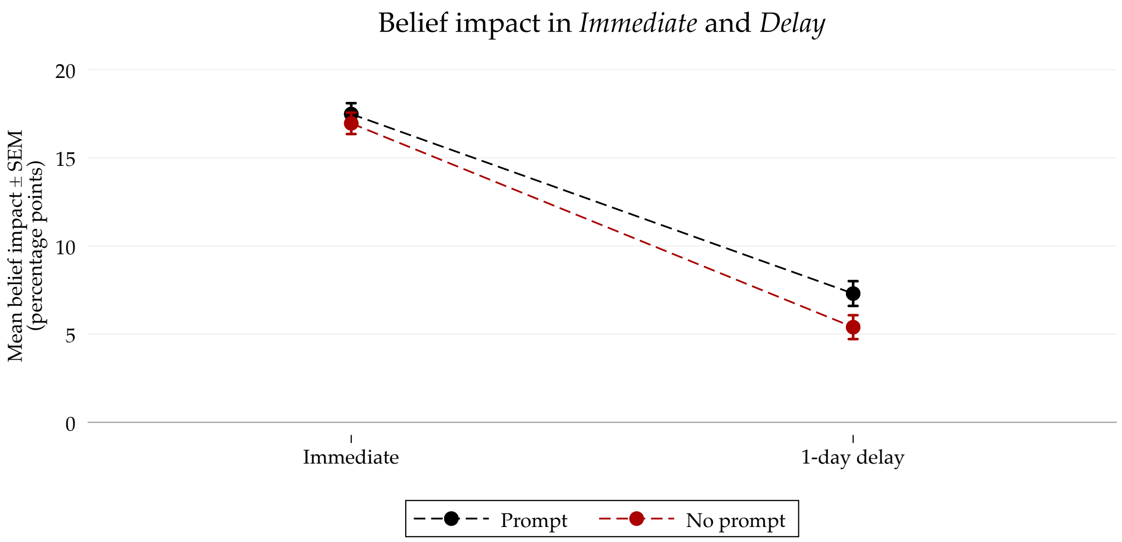
Results. We start by examining whether the prompt intervention was effective in actually inducing participants to imagine reviews and to write them down. The median (mean) number of words participants wrote to describe an imaginary typical review was 22 (23). The text responses indicate that the vast majority of participants made a significant effort to describe a review, such as in the following excerpt from a response in the *NoStoryPrompt* condition about a negative videogame review:

> *The gameplay was sub-par and glitched randomly. The graphics compared the trailer to the actual gameplay were very different giving the impression that the gameplay will have 3D style graphics while in reality, it had very old-school-style graphics [...].*

For ease of exposition, Figure A.8 pools respondents in *NoStoryPrompt* and *StatisticPrompt*, as well as the *NoStory* and *Baseline* conditions.[10] The top panel of Figure A.8 shows results on belief impact, while the bottom panel displays results on recall.

[9]The completion rate to the follow-up survey does not differ significantly across treatment groups ($p = 0.90$). The somewhat lower completion rate compared to the baseline experiment can be explained by the fact that part of the experiment took place on the weekend.

[10]Table A.5 shows results separately for all 4 conditions and confirms that the disaggregated results are similar.



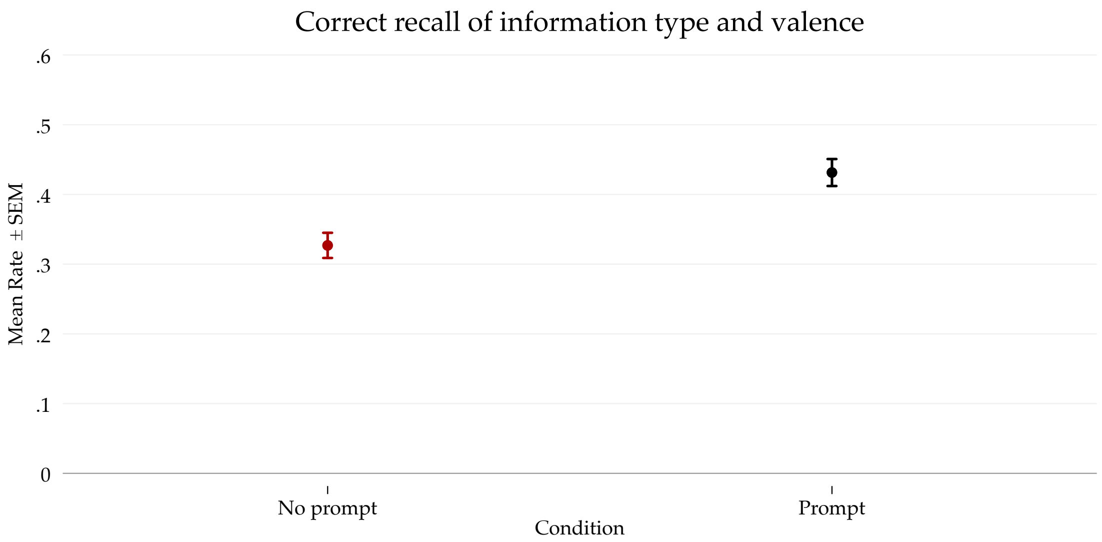


Figure A.7: Belief impact and recall in Robustness Experiment 5 (666 respondents). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The black markers illustrate belief impact and recall for *Prompt*, while the red markers illustrate belief impact and recall for *NoPrompt*. Whiskers indicate one standard error of the mean.

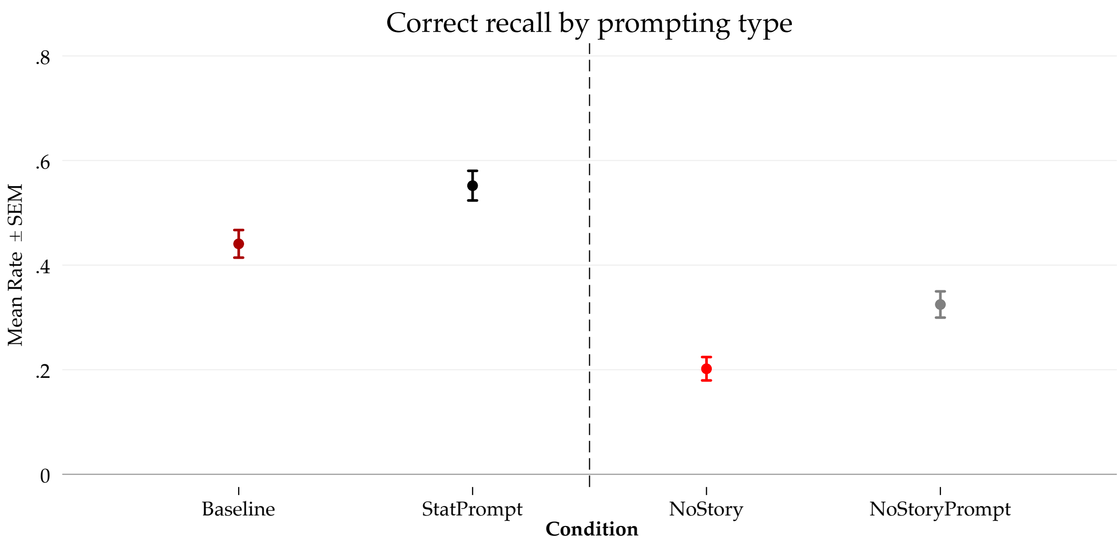


Figure A.8: Belief impact and recall in Robustness Experiment 5: The role of associations (666 respondents). The panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The dark red markers illustrate belief impact and recall for *Baseline*, while the light red markers illustrate belief impact and recall for *NoStory*. The black markers illustrate belief impact and recall for *StatPrompt*, while the gray markers illustrate belief impact and recall for *NoStoryPrompt*. Whiskers indicate one standard error of the mean.

Table A.5: Prompting Experiment: belief impact and recall

	Dependent variable:					
	Belief Impact			Combined Recall		
Sample:	Pooled (1)	Stat (2)	NoStory (3)	Pooled (4)	Stat (5)	NoStory (6)
Delay	-11.5*** (0.97)	-14.7*** (1.31)	-7.95*** (1.39)			
Prompt	-0.97 (1.19)	-1.47 (1.54)	1.00 (1.50)	0.20*** (0.03)	0.14*** (0.05)	0.26*** (0.05)
Delay × Prompt	3.35** (1.34)	4.22** (1.93)	1.90 (1.83)			
Control Mean	14.47	21.57	6.66	0.19	0.22	0.16
Observations	1332	662	670	1332	662	670
R^2	0.09	0.15	0.06	0.05	0.02	0.08

Notes. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Prompt* is an indicator taking value 1 for respondents who were prompted to imagine a typical review when provided with statistical information. All columns pool *Immediate* and *Delay*. Columns (1) and (4) include all respondents. Column (2) and (4) include respondents who received statistics. Columns (3) and (6) include observations who received information on a single review. Columns (1) to (3) display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Columns (4) to (6) display the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Starting with belief impact, we find that, reassuringly, beliefs in *Immediate* are not meaningfully different across the *Prompt* and the *NoPrompt* conditions. Yet, in *Delay*, average belief impact for respondents in the *Prompt* conditions is 7.30 p.p. (s.e. 0.70) compared to only 5.40 p.p. (s.e. 0.68) in *NoPrompt*. This treatment difference in *Delay* is statistically significant ($p < 0.01$). Column (1) of Table A.5 reveals that the difference-in-differences (difference in slopes) is also statistically significant ($p < 0.05$).

These patterns for *Delay* beliefs are underscored by results on recall. The bottom panel of Figure A.8 shows that recall accuracy is 43.14 percent for respondents in *Prompt*, compared to only 32.69 percent in the conditions without prompt. Table A.5 reveals that these differences are highly statistically significant when comparing respondents in the *StatisticPrompt* and *Baseline* conditions, as well as when comparing respondents in the *NoStoryPrompt* and *NoStory* conditions.

While the effect size from this experiment is smaller than in our baseline evidence, it is worth bearing in mind that approximately 17% of respondents did not fully engage with the prompt. Consistent with the idea that engagement with the prompt matters, respondents with above median text length in the prompt are 11 percentage points more likely to correctly recall the information than those respondents with a below median text length.

Recall of binary quantitative information. One result that emerges from this experiment is that in the absence of a prompt to encode additional qualitative information, people perform similarly at recalling information about a binary variable as they do at recalling a statistic. Specifically, Table A.5 reveals that correct recall among respondents in the *NoStoryPrompt* condition is 16 percent and thus, if anything, lower compared to correct recall of statistical information in the *Baseline* condition (22 percent).

A.8 Baseline Results including Participants affected by Coding Error

52 participants of the Baseline Experiment were excluded from the main analysis due to a coding error. When the drawn statistic corresponded to a share of 100% positive reviews, no numbers were displayed on the screen. Here, we repeat the analysis of the Baseline Experiment including these participants. All results remain virtually unchanged.

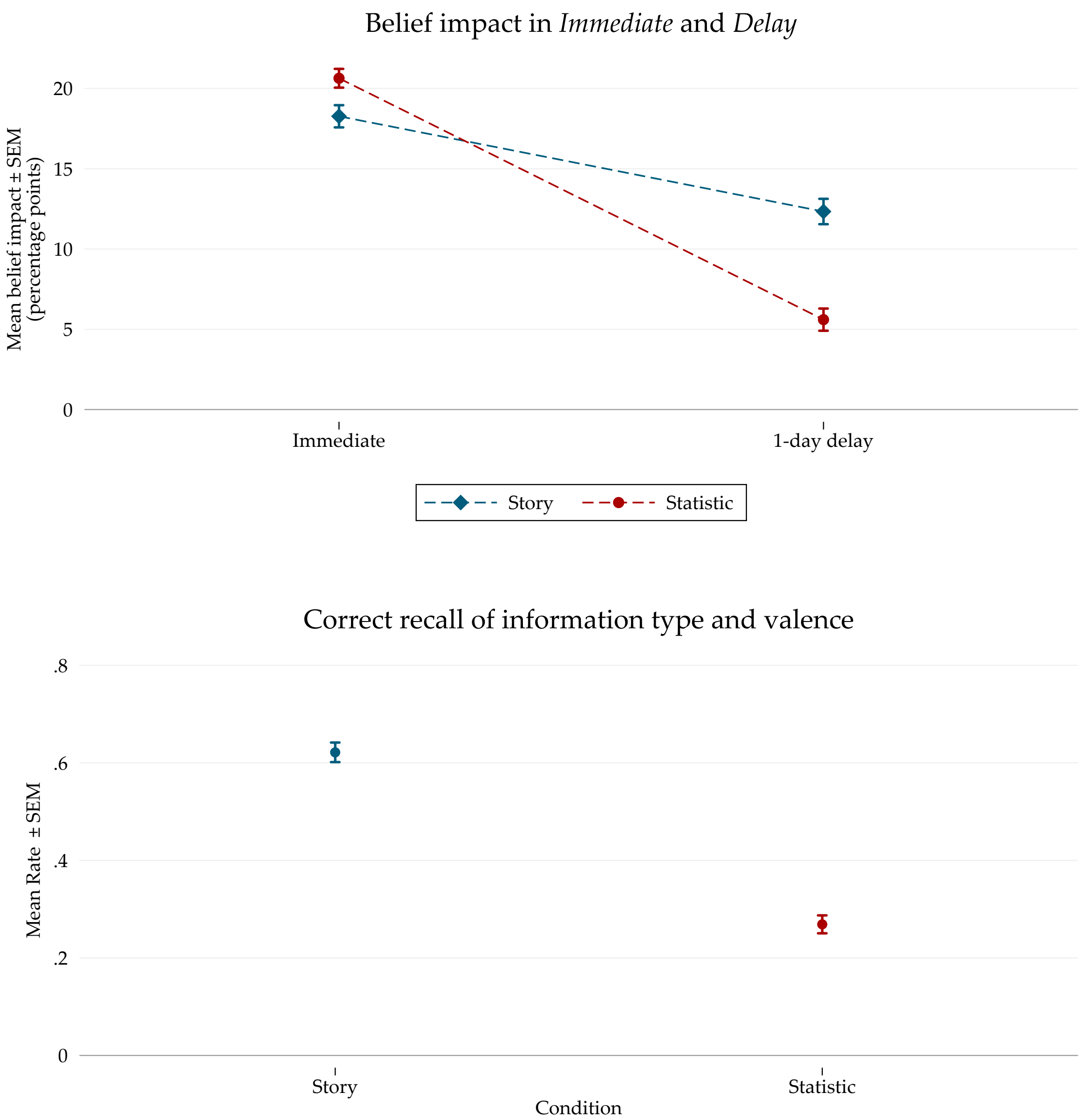


Figure A.9: The story-statistic gap in the baseline experiment including observations of 52 participants affected by the coding error (hence 985 respondents in total). The top panel displays belief impact in percentage points, separately for conditions *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The red markers refer to statistics, while the blue markers refer to stories. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. Whiskers indicate one standard error of the mean.

Table A.6: The story-statistics gap in memory (including participants affected by coding error)

	Dependent variable:			
	Belief Impact			Combined Recall
Sample:	Immediate	Delay	Pooled	Consistent
	(1)	(2)	(3)	(4)
Story	-2.37*	6.73***	-2.37**	0.35***
	(1.23)	(1.48)	(1.01)	(0.03)
Delay			-15.0***	
			(0.90)	
Story × Delay			9.10***	
			(1.28)	
Control Mean	20.63	5.60	20.63	0.27
Observations	1168	1168	2336	1168
R^2	0.54	0.52	0.43	0.65

Notes. This Table uses responses from the *Story* and *Statistic* condition, including those of 52 participants affected by a coding error. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Story* takes value 1 for respondents who received a story for a given product, and zero otherwise. *Statistic* takes value 1 for respondents who received a statistic for a given product, and zero otherwise. Columns (1), (2) and (4) include respondents who received consistent stories. Column (3) pools *Immediate* and *Delay*. Columns (1) to (3) display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Column (4) displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Additional Tables and Figures

Table A.7: Overview of data collections

Collection	Sample	Baseline Treatments	Additional Treatments	Main outcomes	Link to pre-analysis plan
Baseline experiments					
Baseline Experiment	Prolific (933 respondents)	3 products: story, statistic, no information	For story treatment 3 different types of qualitative features: consistent, neutral, mixed.	Beliefs in immediate and delay; Open-ended recall in delay	`https://aspredicted.org/e5mw7.pdf`
Statistics with Qualitative Content	Prolific (673 respondents)	3 products: statistic with qualitative content, statistic without qualitative content, no information	None	Beliefs in immediate and delay; Structured incentivized recall in delay	`https://aspredicted.org/2RB_H9J`
Main Mechanism Experiments					
Mechanism Experiment 1: Cue-Target Similarity	Prolific (627 respondents)	3 products: story, statistic, no information	**High Similarity**: The Italian Restaurant "Napoli". **Low Similarity 1:** An Eatery **Low Similarity 2:** Mr. Jones	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/D21_PW7`
Mechanism Experiment 2: Cue-Non-Target Similarity	Prolific (505 respondents)	3 venues: food truck, sports stadium and amusement park	**Low Interference**: 3 distinct stories. **High Interference**: same story about target product, but now similar stories about other products.	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/4Q6_3YD`
Robustness					
Robustness experiment 1: Uninformative Qualitative Content	Prolific (714 respondents)	3 products: story, statistic, no information	None	Beliefs in immediate and delay; Structured incentivized recall in delay	`https://aspredicted.org/B49_DB1`
Robustness Experiment 2: The role of Decoy Information	Prolific (1,513 respondents)	3 products (1 target and 2 non-target products): Target: Either Story or Statistic	Non-Target products: Either 2 stories, 2 statistics or 2 times no information	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/qy3wq.pdf`
Robustness Experiment 3: Number of product scenarios	Prolific (1,018 respondents)	1 product: Statistic or story; 3 products (statistic, story, no info; 6 products: statistic, story and 4 times no info	None	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/as7i7.pdf`
Robustness Experiment 4: Question Format and statistic display	Prolific (818 respondents)	3 products: story, statistic, no information	**Likelihood**: elicitation from baseline. **Fraction**: elicitation about the percentage of positive reviews **Statistic number:** number of positive reviews. **Statistic percent**: percentage of positive reviews.	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/ZFF_88V`
Robustness Experiment 5: The role of associations	Prolific (666 respondents)	3 products. Decoys: Story and no information; Target varies across treatments	**Baseline**: statistic without prompt; **Prompt**: statistic with prompt; **No story**: Single review without prompt; **No story prompt**: Single review with prompt	Beliefs in immediate and delay; Structured recall task	`https://aspredicted.org/v9gk7.pdf`

This Table provides an overview of the different data collections. The sample sizes refer to the final sample of respondents that completed both waves and satisfied the pre-specified inclusion criteria for each of our collections.

Table A.8: The story statistics gap: page time heterogeneity

	Dependent variable:			
	Belief Impact			Combined Recall
Sample:	Immediate	Delay	Pooled	Consistent
	(1)	(2)	(3)	(4)
Story	-4.61***	4.23***	-4.61***	0.32***
	(1.30)	(1.57)	(1.30)	(0.04)
Delay			-16.3***	
			(1.13)	
Story × Delay			8.84***	
			(1.57)	
Slow	-0.81	0.12	-0.81	0.059
	(1.16)	(1.45)	(1.16)	(0.04)
Story × Slow	2.10	4.20*	2.10	0.0031
	(1.80)	(2.22)	(1.80)	(0.05)
Delay × Slow			0.93	
			(1.60)	
Story × Delay × Slow			2.10	
			(2.30)	
Control Mean	22.15	5.87	22.15	0.26
Observations	1094	1094	2188	1094
R^2	0.01	0.04	0.12	0.11

Notes. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Story* takes value 1 for respondents who received a story for a given product, and zero otherwise. *Slow* is an indicator taking value 1 for respondents whose response time was above the median in their condition. Columns (1), (2), (3) and (4) include respondents who received consistent stories. Column (3) pools *Immediate* and *Delay*. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Columns (4) displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Statistics with Qualitative Content

	Dependent variable:			
	Belief Impact			Correct Recall
Sample:	Immediate	Delay	Pooled	All
	(1)	(2)	(3)	(4)
Statistic with Context	3.41***	8.41***	3.41***	0.37***
	(0.95)	(1.25)	(0.78)	(0.02)
Delay			-18.8***	
			(0.87)	
Statistic with Context × Delay			5.00***	
			(1.15)	
Control Mean	21.95	3.13	21.95	0.21
Observations	1346	1346	2692	1346
R^2	0.56	0.61	0.51	0.14

Notes. This Table uses responses from the *Statistics with Qualitative Content*. OLS estimates, standard errors clustered at the participant level in parentheses. *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Statistic with Qualitative Content* takes value 1 for respondents who received a statistic with additional qualitative content for a given product, and zero otherwise. All columns include respondents who received consistent stories. Column (3) pools *Immediate* and *Delay*. Column (4) includes all observations. Columns (1) to (3) display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Column (4) displays the fraction of respondents correctly recalling the type and direction of information they received in the survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Cue-target similarity and similarity of cue to non-target information: Mechanism Experiments 1 and 2

	Dependent variable:			
	Belief Impact		Combined Recall	
Sample:	Cue-target sim.	Cue-non-target sim.	Cue-target sim.	Cue-non-target sim.
	(1)	(2)	(3)	(4)
Low Similarity 1	1.81		-0.093**	
	(1.43)		(0.04)	
Low Similarity 2	1.93		-0.41***	
	(1.48)		(0.04)	
High Interference		-0.10		-0.17***
		(1.34)		(0.04)
Delay × Low Similarity 1	-3.67**			
	(1.69)			
Delay × Low Similarity 2	-7.20***			
	(1.75)			
Delay × High Interference		-3.85**		
		(1.58)		
Delay	-5.68***	-6.66***		
	(1.10)	(1.13)		
Control Mean	14.9***	16.5***	0.79***	0.48***
	(0.98)	(1.02)	(0.03)	(0.03)
Observations				
R^2	1251	1010	627	505
r2	0.09	0.08	0.13	0.03

Notes. Columns (1) and (3) show data from Mechanism Experiment 1 (627 respondents), while columns (2) and (4) show data from Mechanism Experiment 2 (505 respondents). *Delay* is an indicator taking value 1 for respondents in the follow-up survey, and value 0 for respondents in the baseline survey. *Low Similarity 1* takes value 1 for respondents in Mechanism Experiment 1 who received the Eatery cue with low similarity to the story content, and zero otherwise. *Low Similarity 2* takes value 1 for respondents in Mechanism Experiment 1 who received the Mr. Jones cue with low similarity to the story content, and zero otherwise. *High Interference* takes value 1 for respondents in Mechanism Experiment 2 who received non-target stories with a high similarity to the cue. Columns (1) and (3) include respondents' answers in the "restaurant" scenario of Mechanism Experiment 1. Columns (2) and (4) include respondents' answers in the "food truck" scenario of Mechanism Experiment 2. Columns (1) and (2) display results on belief impact. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. Columns (3) and (4) display the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. OLS estimates, standard errors clustered at the respondent level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Summary statistics

	Baseline Experiments		Mechanisms		Robustness				
Experiment:	New Baseline	Context	Cue-Target Sim	Cue-Non-Target Sim	Uninformative	Decoy	Product	Format	Association
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Male	0.542	0.516	0.518	0.545	0.517	0.504	0.496	0.510	0.560
Age (years)	39.921	42.212	40.394	41.152	43.189	40.792	37.351	36.954	39.851
College	0.616	0.645	0.675	0.636	0.597	0.645	0.619	0.630	0.596
Employed	0.747	0.774	0.778	0.752	0.791	0.784	0.779	0.758	0.746
Observations	933	673	627	505	714	1,513	1,018	818	666

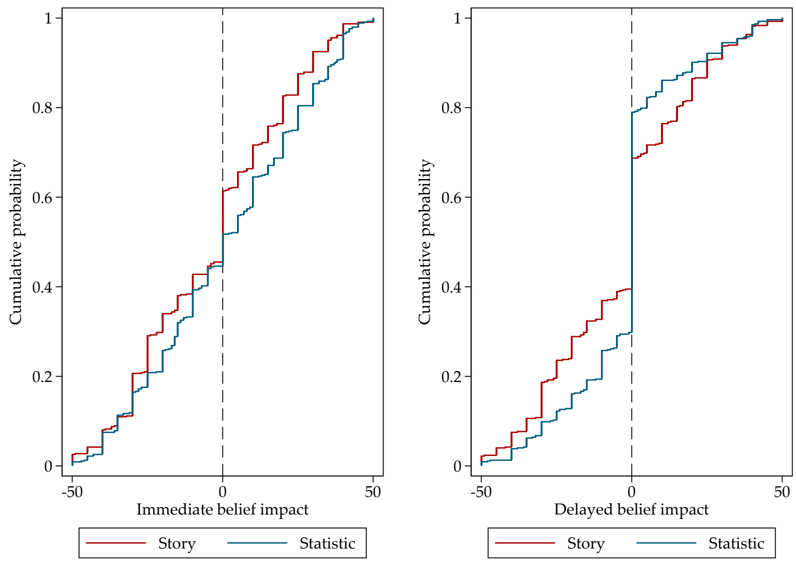
Notes. Summary statistics. We include all participants who completed both the baseline and the follow-up survey. *Male* is an indicator taking value 1 if the respondent identifies as male and 0 else. *Age* is the respondent's age in years. *College* is an indicator taking value 1 if the respondent holds at least a Bachelor's degree and 0 else. *Employed* is an indicator taking value 1 if the respondent is employed and zero for all other respondents. The columns contain observations from each of the following experiments. Column (1): *Baseline Experiment*. Column (2): *Statistics with Qualitative Content*. Column (3): *Mechanism Experiment 1: Cue-Target Similarity*. Column (4): *Mechanism Experiment 2: Cue-Non-Target Similarity*. Column (5): *Robustness experiment 1: Uninformative Qualitative Content*. Column (6): *Robustness Experiment 2: The role of Decoy Information*. Column (7): *Robustness Experiment 3: Number of product scenarios*. Column (8): *Robustness Experiment 4: Question Format and statistic display*. Column (9): *Robustness Experiment 5: The role of associations*.

Table A.12: Attrition by conditions

	Dependent variable:						
	Wave 2 Completion						
Experiment:	Baseline	Cue-Target Sim	Cue-Non-Target Sim	Decoy	Product	Format	Association
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Neutral Story	0.021						
	(0.03)						
Mixed Story	0.026						
	(0.03)						
An Eatery		0.031					
		(0.04)					
Mr. Jones		-0.023					
		(0.04)					
High Similarity			-0.017				
			(0.03)				
Decoy: Story				0.017			
				(0.02)			
Decoy: Statistic				-0.0054			
				(0.02)			
1-Product					-0.014		
					(0.03)		
6-Products					-0.046		
					(0.03)		
Belief: %						0.013	
						(0.03)	
Info: %						0.020	
						(0.03)	
Prompt							-0.033
							(0.03)
Mean Completed	0.68	0.73	0.75	0.76	0.73	0.58	0.46
Observations	1364	912	670	2048	1404	1400	1442
p(Joint Null)	0.65	0.34	0.62	0.60	0.37	0.67	0.21
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes. OLS estimates, standard errors clustered at the participant level in parentheses. *Wave 2 Completion* is an indicator taking value 1 for respondents who completed the follow-up survey, and value 0 who completed the baseline survey only. The columns contain observations from each of the following experiments. Column (1): *Baseline Experiment*. Column (2): *Mechanism Experiment 1: Cue-Target Similarity*. Column (3): *Mechanism Experiment 2: Cue-Non-Target Similarity*. Column (4): *Robustness Experiment 2: The role of Decoy Information*. Column (5): *Robustness Experiment 3: Number of product scenarios*. Column (6): *Robustness Experiment 4: Question Format and statistic display*. Column (7): *Robustness Experiment 5: The role of associations*. The independent variables are indicators for each between-subject condition.

Figure A.10: CDFs: belief impact



Notes: Empirical cumulative distribution functions (CDFs) of belief impact in the *Immediate* (left) and *Delay* (right) conditions. Belief impact is the distance between a stated belief and the prior (50%). The data is from the baseline study. Red lines illustrate data from the Story condition, while blue lines illustrate data from the Statistic condition.

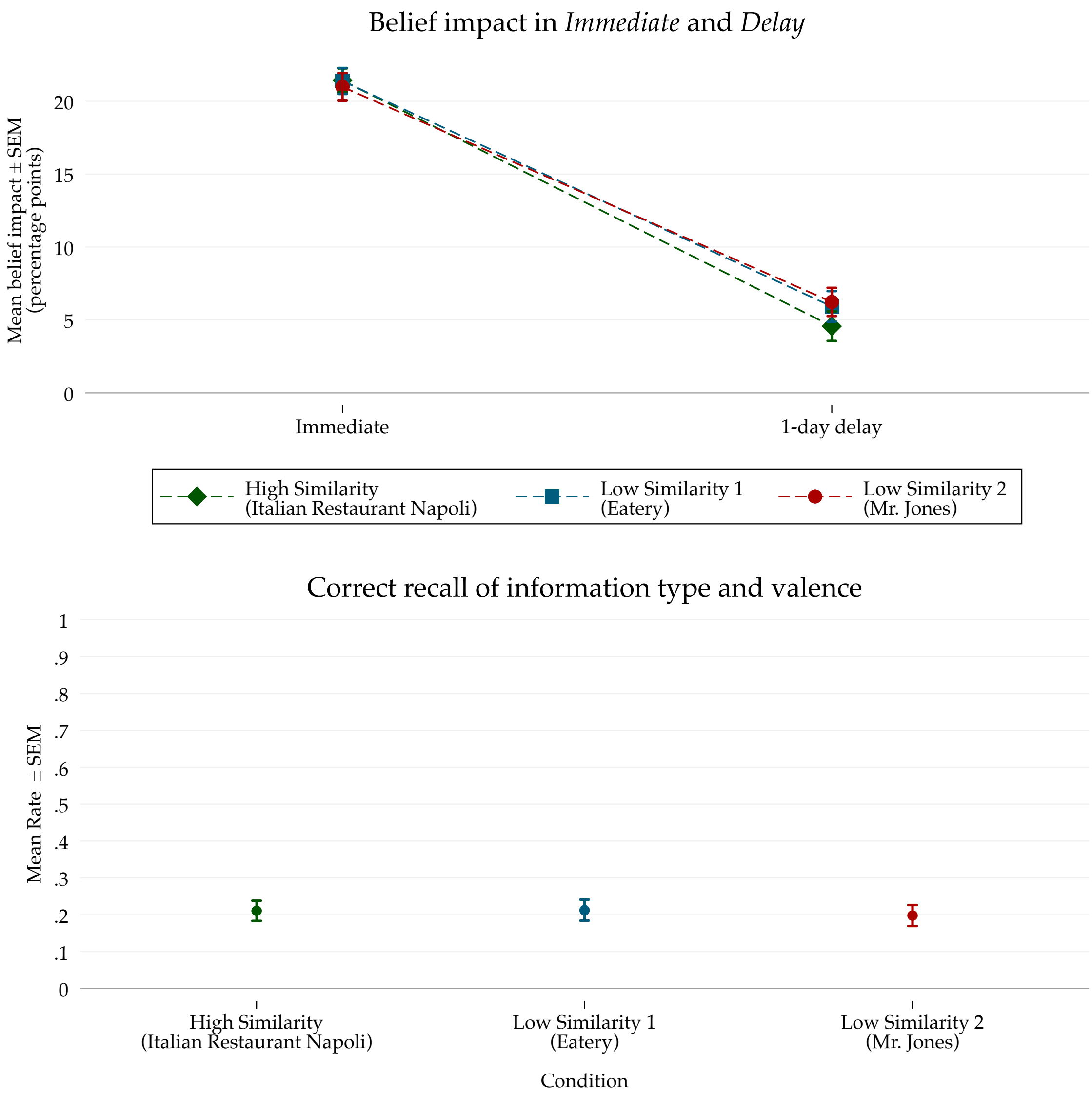


Figure A.11: Belief impact and recall of statistics in the Mechanism Experiment 1: Cue-Target Similarity (627 respondents). The sample consists of statistics only. The top panel displays belief impact in percentage points, separately for each cue. Belief impact is the signed distance between a stated belief and the prior (50%). Belief impact is signed in the direction of the rational update. The bottom panel displays the fraction of respondents correctly recalling the type and direction of information they received in the baseline survey. The blue markers illustrate belief impact and recall for the cue with high similarity, while the green and red markers illustrate belief impact and recall for cues with low similarity. Whiskers indicate one standard error of the mean.

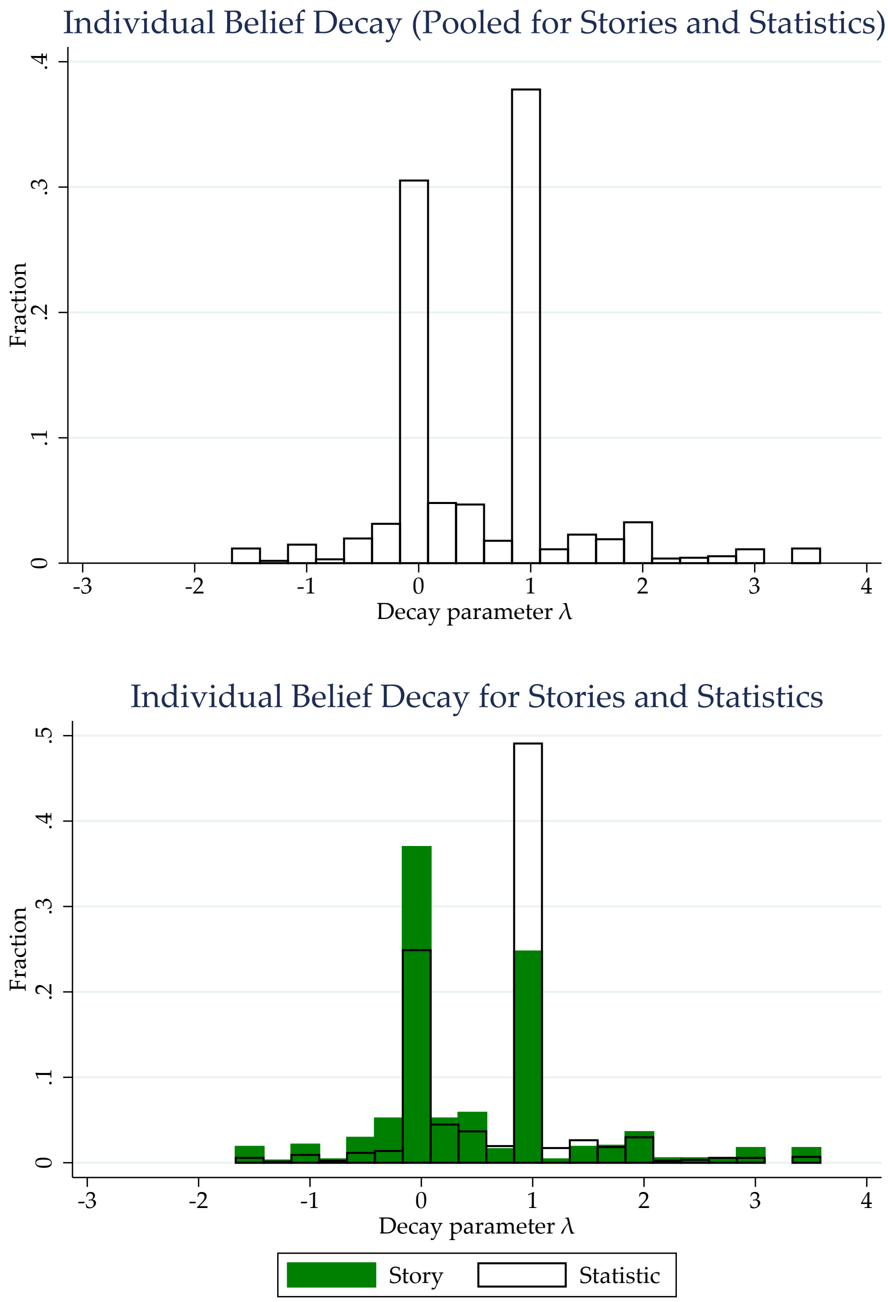


Figure A.12: Individual belief decay parameters λ in the baseline experiment (933 respondents). The sample consists of observations from the story and statistic condition. The parameters are estimated for each subject using $\text{Belief}_{i2} = \lambda \times \text{IgnorancePrior} + (1-\lambda) \times \text{Belief}_{i1}$, where Belief_{i2} is the second-period belief, and where Belief_{i1} is the first-period belief. The distributions were winsorized at the 1% level for exposition. The top panel displays a histogram of the pooled data for both the statistic and story condition, while the bottom panel displays treatment differences.

C Overview of stories

C.1 Baseline stories

Video games (positive) One of the reviews was randomly selected. The selected review is positive. It is written by 23-year-old Julia, who says she absolutely fell in love with the game. The game called "Planet of Conflict", is a novel concept of a multiplayer role-playing game based on World of Warcraft. Julia was blown away by the realistic graphics. This is the very first time she got totally hooked on a game. Julia mentions that she once played Planet of Conflict for 13 straight hours on a weekend because it was so entertaining. "I communicate with a lot of people online through this game, which I love", Julia says. "Planet of Conflict is just something else entirely. I think I'm a gamer now!"

Video games (negative) One of the reviews was randomly selected. The selected review is negative. It is written by 23-year-old Julia, who says she absolutely hates the game. The game called "Planet of Conflict" is an outdated concept of a multiplayer role-playing game based on World of Warcraft. Julia was disappointed by the pixelated graphics. This is the first time she ever got totally bored by a video game. Julia mentions that she almost fell asleep after the first 30 minutes of playing Planet of Conflict because nothing really happened. "I don't communicate at all with people through this game, which I hate", Julia says. "Planet of Conflict is just something else entirely. I don't think I like gaming anymore after this!"

Video games (mixed) One of the reviews was randomly selected. The selected review is [positive / negative]. It is written by 23-year-old Julia, who says she has mixed feelings about the game. The game called "Planet of Conflict" is a novel concept of a multiplayer role-playing game based on World of Warcraft. Julia was disappointed by the pixelated graphics. However, this is the very first time she got totally hooked on a game. Julia mentions that she once played Planet of Conflict for 13 straight hours on a weekend because it was so entertaining. "At the same time, I don't communicate at all with people through this game, which I hate", Julia says. "Planet of Conflict is just something else entirely. I disliked some parts of the game, but it got me excited about gaming!"

Video games (neutral) One of the reviews was randomly selected. The selected review is [positive / negative]. It is written by 23-year-old Julia. The game called "Planet of Conflict" is a multiplayer role-playing game based on World of Warcraft. Julia's review mentioned the graphics. Julia has played many other games before. Julia mentions that she played Planet of Conflict for a while last weekend. “I sometimes communicate with people through this game”, Julia says. She also stated “Planet of Conflict” is comparable to other video games she has played.

Bicycle (positive) One of the reviews was randomly selected. The selected review is positive. It was provided by Rufus, who is a passionate hobby cyclist. His experience with the bike, a large blue trekking model called “Suburban Racer”, could not have been any better. The bike was delivered after just 4 days. It didn’t require any assembly. The bike is extremely light; riding up his first little hill Rufus felt like he was flying. Rufus mentions that the bike is of exceptional quality. He wrote the report almost 5 years after purchasing it and still hasn’t experienced any problems that required repair. “If you want a worry-free cycling experience, this is the one”, Rufus states.

Bicycle (negative) One of the reviews was randomly selected. The selected review is negative. It was provided by Rufus, who is a passionate hobby cyclist. His experience with the bike, a large blue trekking model called “Suburban Racer”, could not have been any worse. The bike was delivered more than 7 months late. It required 13 hours of assembly work. The bike is extremely heavy; riding up his first little hill Rufus felt like he was crawling. Rufus mentions that the bike is of awful quality. He wrote the report no more than 3 months after purchasing it and has already experienced a number of problems that required expensive repair. “If you want a worry-free cycling experience, definitely go for something else”, Rufus states.

Bicycle (mixed) One of the reviews was randomly selected. The selected review is [positive / negative] . It was provided by Rufus, who is a passionate hobby cyclist. His experience with the bike, a large blue trekking model called “Suburban Racer”, was mixed. The bike was delivered after just 4 days. However, it required 13 hours of assembly work. The bike is extremely light; riding up his first little hill Rufus felt like he was flying. At the same time, Rufus mentions that the bike is of low quality. He wrote the report no more than 3 months after purchasing it and has already experienced a number of problems that required expensive repair. “If you want a worry-free cycling experience, not sure this is the right bike for you”, Rufus states.

Bicycle (neutral) One of the reviews was randomly selected. The selected review is [positive / negative] . It was provided by Rufus, who is a hobby cyclist. He describes his experience with the bike, a large blue trekking model called “Suburban Racer”. The bike was delivered around the time predicted by the manufacturer. It required some assembly work. The bike has a typical weight compared to other bikes. Rufus' review described the quality of the bike. He wrote the report a while after purchasing it and has made some repairs in the meantime.

Restaurant (positive) One of the reviews was randomly selected. The selected review is positive. It was provided by Justin. He and his friend had a wonderful experience at the Japanese restaurant called "Sushi4Ever". They ordered the sushi taster. The raw fish looked fresh and all sushi was expertly prepared. Justin was impressed by the authentic taste that reminded him of his holiday in Japan. The service was exquisite: his waiter was polite, highly attentive and the food was served promptly. After Justin had paid, the waiter served a traditional Japanese drink on the house that Justin had never heard of before and loved. As they left the restaurant, Justin was very happy and thought to himself "I'll be back!"

Restaurant (negative) One of the reviews was randomly selected. The selected review is negative. It was provided by Justin. He and his friend had an awful experience at the Japanese restaurant called "Sushi4Ever". They ordered the sushi taster. The raw fish looked stale and the sushi rolls were falling apart on the plate. Justin was disappointed by the Western taste that was very different from what he remembered from his holiday in Japan. The service was poor: his waiter was rude, not attentive and the food was served after a long wait. After Justin had paid, the waiter insisted on them leaving their table immediately. As they left the restaurant, Justin was very annoyed and thought to himself "I definitely won't be back!"

Restaurant (mixed) One of the reviews was randomly selected. The selected review is [positive / negative] . It was provided by Justin. He and his friend had a mixed experience at the Japanese restaurant called "Sushi4Ever". They ordered the sushi taster. The raw fish looked fresh and all sushi was expertly prepared. Justin was impressed by the authentic taste that reminded him of his holiday in Japan. The service, however, was poor: his waiter was rude, not attentive and the food was served after a long wait. After Justin had paid, the waiter insisted on them leaving their table immediately. As they left the restaurant, Justin was conflicted and thought to himself "Not sure whether I'll go again."

Restaurant (neutral) One of the reviews was randomly selected. The selected review is [positive / negative]. It was provided by Justin. Justin and his friend describe their experience at the Japanese restaurant called "Sushi4Ever". They ordered the sushi taster. The menu included raw fish and a variety of sushi rolls. Justins' review describes the taste of the sushi. He mentions the service, writes about how attentive the waiter was and how long they had to wait for the food. After Justin had paid, the waiter served a traditional Japanese drink. As they left the restaurant, Justin thought about whether he would come back to the restaurant or not.

C.2 Mechanism Experiment: Cue-Target Similarity

C.2.1 Prompts

- The Italian restaurant "Napoli"
- An eatery
- "Mr. Jones"

Restaurant (positive) One of the reviews was randomly selected. The selected review is positive. It was provided by Luigi. He and his friend had a wonderful experience at the restaurant. They both ordered pizza. It was expertly prepared in Neapolitan style, and the mozzarella tasted extremely fresh. Luigi was impressed by the authentic taste that reminded him of his holiday in Naples, Southern Italy. For dessert they ordered the restaurant's favorite, special Italian Tiramisu, which was mouth-watering. After Luigi had paid, the waiter served a traditional Italian drink, Limoncello, that Luigi had never heard of before and loved. As they left the restaurant, Luigi was very happy and thought to himself "I'll be back!"

Restaurant (negative) One of the reviews was randomly selected. The selected review is negative. It was provided by Luigi. He and his friend had an awful experience at the restaurant. They both ordered pizza. The pizza dough was extremely dry and bland, and the mozzarella had an unappealing bitter aftertaste. Luigi was disappointed by the unauthentic taste that was very different from what he remembered from his holiday in Naples, Southern Italy. For dessert they ordered the restaurant's favorite, special Italian Tiramisu, which tasted acidic and slightly revolting. After Luigi had paid, the waiter insisted on them leaving their table immediately. As they left the restaurant, Luigi was very annoyed and thought to himself "I definitely won't be back!"

C.3 Mechanism Experiment: Similarity of Cue to non-Target Information

C.3.1 High Similarity Treatment

Food truck One of the reviews was randomly selected. The selected review is positive. It was provided by Justin, who had a hot dog at the food truck and loved it. A sign claimed to serve "a bite of heaven for just a few bucks." The juicy sausage hissed and sizzled on the grill as delicious aromas filled the air. Once golden brown, it was nestled inside a slightly toasted bun, soft as a cloud. The toppings were a gourmet surprise: caramelized onions simmered in bourbon, creamy avocado mayo, spicy jalapeno relish, and a sprinkle of crumbled feta cheese. Justin's first bite was an epiphany. The sausage was perfectly seasoned, with a hint of smokiness, while the toppings complemented each other perfectly – the sweetness of the onions, the creaminess of the mayo, the tang of the relish, and the salty kick of feta. Justin savored every bite of that hot dog. It was an unexpected gourmet experience that was nothing short of legendary.

Sports stadium One of the reviews was randomly selected. The selected review is negative. It was provided by Darren, who had a hot dog at the stadium and hated it. A sign claimed to serve "the pinnacle of flavor for mere pennies." The shriveled hot dog cracked and smoked on the grill, creating a revolting smell. Once charred black, it was slammed inside a rock-hard bun, dry as desert sand. The toppings were a nasty shock: overripe relish oozing with slime, rancid garlic mayo, wilted lettuce, and a sprinkle of stale blue cheese. Darren's first bite was pure regret. The hot dog tasted burnt beyond belief, while the toppings clashed in an awful way – the sourness of the relish, the bitterness of the mayo, the blandness of the lettuce, and the moldy hint of cheese. Darren regretted every bite of that hot dog. It was a disgusting culinary experience that was nothing short of a disaster.

Amusement park One of the reviews was randomly selected. The selected review is negative. It was provided by Lucas, who tried a hot dog in the amusement park and was shocked. A sign boasted "unforgettable taste for a dime." The skinny hot dog shriveled and popped on the grill, releasing odors that turned heads away. Once burnt to a crisp, it was carelessly thrown into a stale bun, crumbly and old. The toppings were an unfortunate surprise: soggy sauerkraut dripping with excess water, overly pungent mustard, limp pickles, and a dab of cream cheese gone bad. Lucas' initial bite was one of dismay. The hot dog tasted like rubber, and the toppings jumbled into a mess of sensations – the wateriness of the sauerkraut, the overpowering punch of the mustard, the lifelessness of the pickles, and the sourness of the cheese. Lucas could hardly finish that hot dog. It was a culinary disaster that was memorably underwhelming.

C.3.2 Low Similarity treatment

Food truck One of the reviews was randomly selected. The selected review is positive. It was provided by Justin, who had a hot dog at the food truck and loved it. A sign claimed to serve “a bite of heaven for just a few bucks.” The juicy sausage hissed and sizzled on the grill as delicious aromas filled the air. Once golden brown, it was nestled inside a slightly toasted bun, soft as a cloud. The toppings were a gourmet surprise: caramelized onions simmered in bourbon, creamy avocado mayo, spicy jalapeno relish, and a sprinkle of crumbled feta cheese. Justinâs first bite was an epiphany. The sausage was perfectly seasoned, with a hint of smokiness, while the toppings complemented each other perfectly – the sweetness of the onions, the creaminess of the mayo, the tang of the relish, and the salty kick of feta. Justin savored every bite of that hotdog. It was an unexpected gourmet experience that was nothing short of legendary.

Sports stadium One of the reviews was randomly selected. The selected review is negative. It was provided by Darren, who attended a football game in a sports stadium and left deeply frustrated. A banner boasted “unparalleled experience for true fans.” The seating was cramped and creaked with every move, eliciting whispered complaints from spectators. Once seated, he strained to get a decent view, his line of sight blocked by a poorly placed pillar. The misgivings were manifold: an overhead screen that flickered intermittently, the blaring of mismatched commentary, unexpected seat vibrations, and a finale of a spilled drink from the row above. Darren’s enthusiasm waned rapidly. The stadium, instead of amplifying the football game, detracted from it, with one annoyance after another – the obstructed view, the distorted sound, the jarring vibrations, and the sticky mess on his back. Darren regretted attending that match. It was a sporting experience that was disappointingly off-mark.

Amusement park One of the reviews was randomly selected. The selected review is negative. It was provided by Lucas, who visited the amusement park and was utterly disappointed. A sign falsely promised “adventures beyond imagination for thrill-seekers.” Once strapped in, he was elevated to uncomfortable heights, making the rest of the park look tiny and run-down in the distance. The experiences were underwhelming: a dark, dimly lit tunnel, the abrasive gust of wind, stomach-churning drops, and an unexpected, chilling water splash at the end. Lucas’ heart filled with regret. The roller coaster was a jarring blend of unease and dismay, and the elements combined into a confusing mess –

the dimness of the lights, the nausea from the descent, the jolt of the unexpected, and the cold splash at the end. Lucas wished he could forget every moment of that visit. It was a forgettable misadventure that marked a low point in his summer.

D Implementation Details on the Experiments

Randomization. In the baseline survey, the randomization is implemented by drawing true fractions of positive reviews for the video game, the restaurant and the bicycle i.i.d. uniformly over [0,1]. The total number of reviews is always fixed at 14, 19 and 17 respectively. The lowest fraction is then assigned a "negative" signal direction, while the highest is given a "positive" direction. The product with the median fraction is assigned to the "no information" treatment, which doesn't have a direction. Finally, the type of signal for the two other products is drawn by assigning "story" and "statistic" or "statistic" and "story" to the lowest and highest respectively, each with probability 1/2.

For the product with the "story" signal, the review is either "consistent", "mixed" or "neutral" (cf. Section A.2) with probabilities 0.6, 0.2 and 0.2. For the "statistic" signal, a signal fraction is drawn as $s \sim \mathscr{U}[0, 0.5]$ if the direction is negative and $s \sim \mathscr{U}[0.5, 1]$ if it is positive. Since the signal is indicated as "out of b randomly drawn reviews, a are positive", we chose a and b to minimize $|a/b - s|$, with a integer and $b \in \{4, 5, 6, 7, 8, 9, 10, 11\}$. In case of ties, we favor lower denominators to increase variability. Moreover, we impose that $a/b < 0.5$ or $a/b > 0.5$ depending on the direction.

E Coding Manual for data on open-ended recall

Free-form responses are provided together with subject identifier and information on the product and the type of information received (story, statistic or no info, plus whether the info was positive or negative) in an Excel sheet. All of the below should be coded as binary variables, 1 for presence of a phenomenon in the text and blank for its absence. People may express uncertainty “maybe”, “could be”. Always count this as if people would be stating the same statement with certainty.

Table A.13: Coding Manual for data on open-ended recall data

Category	Explanation	Examples
Lack of memory	Statement that participants do not recall whether and what information they received. This includes instances in which a participant remembers the product, but not whether and what information they received. This does not include statements like "I remember that I received no additional information" or "I don't think I received any additional information about the bicycle" when they actually received no info. Sometimes, it may be hard to distinguish between participants indicating "they donât remember" and âthey remember getting no additional informationâ, e.g., when just stating âNoneâ. It can help looking at the subjectâs two other responses.	"I do not have any recollection about this product/scenario." "I cannot remember anything"
Mention type of information	They mention whether they received a single review, multiple reviews or no information.	"For this product I received no additional information." "I received information on multiple reviews" "There was one review about the videogame. [Details about the review...]"
Misremember type of information	State that received a different type of information than they truly did.	"I received information on a number of reviews." [When in reality, they received a story about a single review]
Mention valence	Response indicates positive or negative tendency. This can be about the majority of reviews being pos/neg, a single review categorized as positive/negative, or about the implicit valence of qualitative features without saying positive/negative.	"The information was mostly positive." "The review was negative." "The bike was of high quality."
Misremember valence	State that information was positive (negative), when it was really negative (positive). This does not include misremembering the exact number of positive reviews of a statistic, as long as the remembered number points in the same direction (positive/negative) as the true one.	"The information was mostly positive." [When the actual information provided was a majority of negative reviews]
Confusion	Answer exclusively talks about things unrelated to the scenario in question, e.g., repeating general instructions, talking about the task in general terms, or talk about what they remember for a different scenario.	
Recall stat correctly	Statements of specific numbers of positive reviews, or total reviews received. Only indicate this if the remembered numbers are correct!	"Out of the 11 sampled reviews 2 were positive and 9 were negative."
Mention qual. factors	Mention specific qualitative elements from a story. This needs to be specific, i.e., does not include âI remember reading information about a personâs review which was really positive.â	"I think they took the bicycle out on hilly terrain, or on some sort of holiday or outing."
Mention first	This is only about a specific order: Mention specific qualitative factors before indicating anything else, such as the valence of the overall review (i.e., whether the review is positive or negative).	"The review selected was from a person that had the bike for 5 years and still thought it worked perfectly. The bike came already assembled. The review selected was a positive review."
Recall immediate belief	Mentions the belief that subject thinks they indicated on the prior day. Indicate independently of whether it is correct.	"In this one, I wrote 85% because it gave a positive review."
Full confusion	Answer exclusively talks about things unrelated to the scenario in question, e.g., repeating general instructions, talking about the task in general terms, or talking about what they remember for a different scenario.	
Misremembering across scenarios	Each participant gave three responses that are in adjacent rows in the Excel file. This category should be coded if the subjectâs response talks about information that is in line with what they received in a different scenario.	Assume the subject got no info for the bicycle, but a positive story for the restaurant, but states the following for the bicycle: "I remember reading about a positive review about the bicycle."
Flag for misc. or uncertain coding	Indicate this if the response includes something distinctive (meaningful) that is not covered by our criteria, or if you are uncertain about your coding I do remember that the first one didnât give much if any information, the second one gave a little more and the third I think gave a little more again.	

This Table provides an overview of the coding scheme. The examples are all taken from the baseline experiment.

F Computing the Bayesian Benchmark

Even though we do not assume Bayesian updating in our model but rather stay agnostic about how agents form their beliefs, it still provides a useful benchmark. In the following, we provide details on the computation of the Bayesian benchmark.

Notation. For a given product p, we call the total number of reviews N, the total number of positive reviews K, the number of observed reviews n and the number of observed positive reviews k. Participants are asked about the probability $\pi := K/N$ of a randomly drawn review being positive. The distribution of N and n has no effect as both are drawn before the experiment. Since we say that the qualitative elements of stories do not convey any inherent information, to a Bayesian a story is simply a statistic with $n = 1$.

Ignorance beliefs. To fix ignorance beliefs, respondents in the experiments are informed that the number of positive reviews is uniformly distributed. Moreover, a uniform distribution over $\llbracket 0, N \rrbracket$ is identical to a beta-binomial distribution with parameters N and $\alpha = \beta = 1$, so that their ignorance belief is:

$$K \sim \mathscr{U}\llbracket 0, N \rrbracket = \text{BetaBinomial}(N, 1, 1) \tag{3}$$

Bayesian beliefs under no-recall. When they recall the wrong memory trace, respondents understand that it is the wrong trace and that they do not have any additional information. Payoff is then maximized by reporting the mean of the ignorance belief, which is:

$$\hat{\pi}_2^{\textit{no-recall}} = \mathbb{E}_{\textit{ignorance}}[\pi] = \frac{1}{2}$$

Bayesian beliefs under recall. When they recall the memory trace, respondents remember that they saw k positive reviews out of n, drawn without replacement from N total reviews, so that the signal follows the hypergeometric conditional distribution:

$$k|K \sim \text{HyperGeometric}(N, K, n) \tag{4}$$

As beta-binomial and hypergeometric distributions are conjugate priors, beliefs about the remaining reviews follow a beta-binomial distribution with parameters $N - n$, $\alpha' := \alpha + k = 1 + k$ and $\beta' := \beta + n - k = 1 + n - k$:

$$K - k|k \sim \text{BetaBinomial}(N - n, 1 + k, 1 + n - k) \tag{5}$$

Note that the average of this distribution is $(N-n)\frac{\alpha'}{\alpha'+\beta'} = (N-n)\frac{k+1}{n+2}$. The payoff is then maximized by reporting the mean of the belief distribution, which is:

$$\hat{\pi}_2^{recall} = \mathbb{E}_{posterior}[\pi] = \frac{k}{N} + \frac{N-n}{N}\frac{k+1}{n+2}.$$

The first term is the certain component and the second term is the uncertain component, i.e., expected number of positive reviews among unobserved reviews. We can note that the expected share of positive reviews among unobserved reviews, $\frac{k+1}{n+2}$, is what we obtain from a simple application of the rule of succession.

Average belief impact of stories and statistics As noted in Section 3.3, the average Bayesian belief movement in our sample is only marginally smaller for stories than for statistics. This reflects two effects: (i) the belief movement from observing a single story is relatively large, (ii) statistics are randomized so that most are rather moderate.

Indeed, for stories, observing one positive story ($k = n = 1$) out of N = 17 total reviews (the average N in our sample) yields a belief update of:

$$\left|\left(\frac{1}{17} + \frac{17-1}{17} \times \frac{1+1}{1+2}\right) - \frac{1}{2}\right| = \left|0.687 - \frac{1}{2}\right| = 0.187$$

This is relatively large, and also virtually identical to the average Bayesian belief movement for stories in our sample (see Section 3.3).

For statistics, this belief movement is larger for extreme draws, but smaller for intermediate draws. To take an extreme example, when k = n/2, the Bayesian belief movement is 0 . Even observing $k = 6$ positive reviews out of $n = 8$ (the average n in our sample) yields:

$$\left|\left(\frac{6}{17} + \frac{17-8}{17} \times \frac{6+1}{8+2}\right) - \frac{1}{2}\right| = \left|0.724 - \frac{1}{2}\right| = 0.224$$

This is not very large, and quite close to the average Bayesian belief movement for statistics in our sample. This explains why, on average across the sample, Bayesian belief movement for statistics is only marginally smaller than for statistics.

G Theoretical Appendix

In the following, we restate the results and provide formal proofs for the model in Section 2.

Recall that the rate of recall between of a trace m^* given a cue c is given by equation

(1):

$$r(m^*, c) = \frac{S(m^*, c)}{\sum_{m \in M} S(m, c)}$$

In our application, the structure of memory traces and cues is determined by the following three assumptions.

Assumption 1. *A memory trace for a scenario has at least one feature present in V^{qual} if a story was received, but none if a statistic or no additional information was received in the baseline experiment.*

Assumption 2. *For any scenario s, the prompt to form a belief triggers a vector c_s that includes non-null features in V^{qual} that are denoted with $A(c)$.*

Assumption 3. *The non-quantitative content of a story delivered in scenario s contains elements that are semantically associated with the scenario. Formally, there is at least one shared feature between $V^{qual}(m_s^{story})$ and $A(c_s)$.*

We start the analysis by stating the connection of recall and belief decay.

Lemma 1. *Conditional on first period beliefs, belief decay is larger if and only if recall is higher and smaller if and only if recall is more likely.*

Proof. This follows from equation (2) which states that

$$\mathbb{E}[|\hat{\pi}_2 - \hat{\pi}_1| \mid \hat{\pi}_1] = (1 - r(m^*, c)) \cdot |\frac{1}{2} - \hat{\pi}_1|$$

where $r(m^*, c)$ is the recall rate. □

Corresponding to the first prediction we have the following.

Proposition 1. *The likelihood of successful recall is higher for stories than for statistics, i.e., $r(m_p^{story}) > r(m_p^{stat})$. Conditional on first-period beliefs, belief decay for stories is lower than for statistics.*

Proof. By Assumption 3 stories and their respective cues share features in V^{qual} and since similarity is increasing in shared features, $S(m_p^{\text{story}}, c_p) > S(m_p^{\text{stat}}, c_p)$ holds. Therefore, the numerator of equation (1) is higher for stories. The denominator of (1) is equal for both treatments and thus the first part of the Proposition is shown. The second part follows from the first one and Lemma 1. □

The formal statement for the second prediction is as follows.

Proposition 2. *Let c_1 and c_2 be two cues and assume m_1^* and m_2^* only differ in the first dimension. If the cue c_1 invokes semantic associations that have a larger overlap with $V^{qual}(m_1^*) = V^{qual}(m_1^*)$ than for c_2, cue-target similarity is higher for c_1, the likelihood of successful recall is greater, and belief decay is lower under c_1.*

Proof. Notice that the number of shared features between a cue and the corresponding memory trace equals 1 (the first dimension is always the same) plus the number of shared features in V^{qual}. If c_1 has a larger overlap with $V^{qual}(m_1^*) = V^{qual}(m_1^*)$, then the number of shared features is higher, which induces a higher cue-target similarity. A higher cue-target similarity means that both the numerator and denominator of (1) rise by the same amount. Since the fraction is not equal to one, this means that recall is greater under c_1 than under c_2. The effect on belief decay follows from Lemma 1. □

The third prediction is proven by the next proposition.

Proposition 3. *All else equal, increasing the similarity between a story in scenario p and a cue for another scenario q decreases the likelihood of successful recall and increases belief decay in q.*

Proof. Increasing the similarity between a the trace m_p and cue c_q will result in an increase of the denominator in equation (1) with $c = c_q$ and $m = m_q$. Therefore, the rate of correct recall about information in scenario q, i.e., $r(c_q, m_q)$, falls. By Lemma 1 belief decay in scenario q rises. □