Narratives about the Macroeconomy

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Motivation

Narratives: causal story/account of why an event occurred.

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Provide a lens through which individuals can interpret data and forecast future developments.

Importance recognized in psychology (e.g., Bruner, 1991), recently also in economics (e.g., Shiller 2017, 2020).

But empirical evidence on econ. narratives remains scarce.

This paper

Goal: Assess nature, consequences, origins of econ. narratives.

High-stakes macroeconomic setting: Rise of US inflation.

- competing narratives
- different implications for future development
- inflation expectations are critical

Research questions

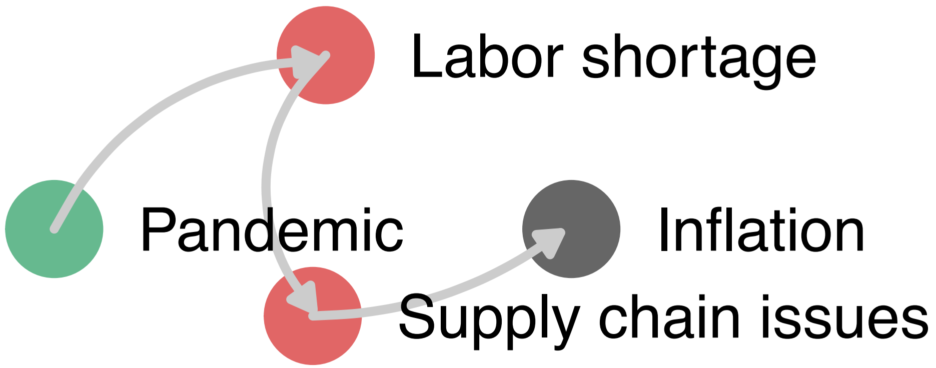
1. What characterizes people's narratives?
2. Do narratives shape inflation expectations?
3. Is the news media an important source of narratives?

Approach

1. **Why has inflation increased?**
   Measure narratives in **open-ended survey responses**

2. Narratives as **causal graphs behind stories**

(As in Eliaz and Spiegler, 2020)



3. **Descriptive surveys**

4. **Experiments** to study
   - **causal effect on expectations**
   - **role of exposure to news media**

Measurement

Samples

Online surveys shortly after BLS inflation data release.

US households

- About 1k per wave, 5 waves, Nov. 21 to October 22.
- Broadly rep. of pop. (income, region, age, gender).
- Recruited with professional survey company (Lucid).

Academic experts

- 111 responses, Nov. 21.
- Invited 2k economists: pub. in top 20 journal (2015–2019) on JEL: E.

Measuring narratives

Why has the inflation rate increased?

In previous years, the US inflation rate has mostly varied between 1.5% and 2.5%. At this rate, a bundle of goods and services that costs $1,000 in one year, would cost between $1,015 and $1,025 in the next year.

Recently, however, the inflation rate has increased. It is now at 6.2%. At this rate, a bundle of goods and services that costs $1,000 in one year, would cost $1,062 in the next year.

Which factors do you think caused the increase in the inflation rate? Please respond in full sentences.

Classifying narratives

Manually code **causal connections** between **key factors**.

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Demand

Gov. spending increased

Loose monetary policy

Pent-up demand

Shift in demand

General/residual demand

Supply

Supply chain disruptions

Labor shortage

Energy crisis

General/residual supply

Other

Pandemic

Gov. mismanagement

Russia-Ukraine war

Price gouging

…

Coding protocol

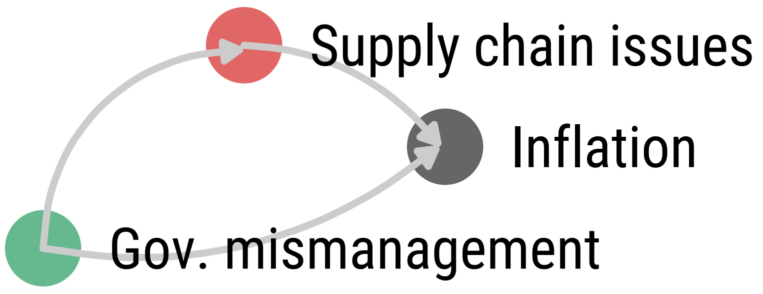
Each response coded by **two independent reviewers**.
Each conflict resolved manually.

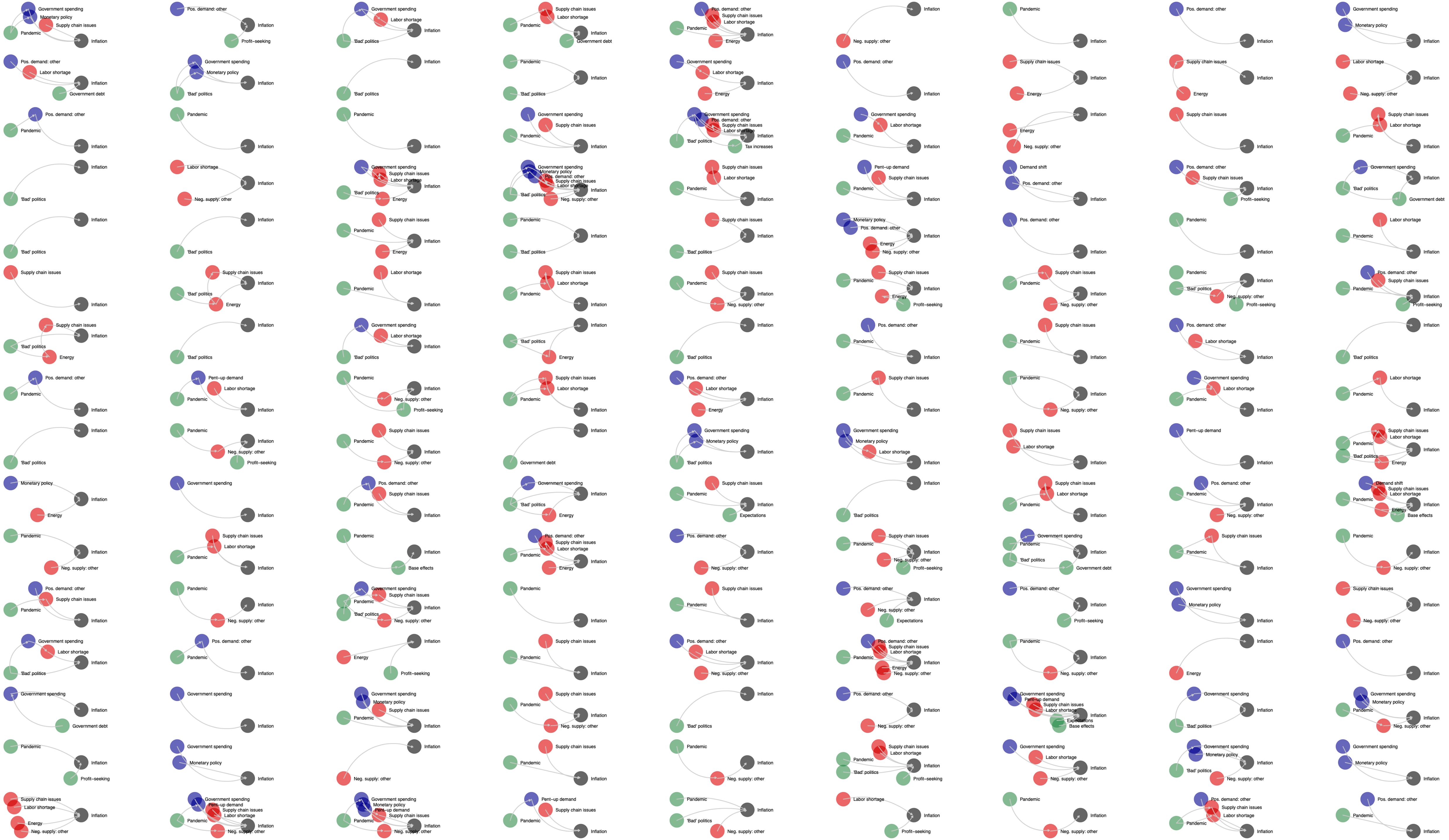
High data quality
Almost all responses contain a narrative.
Households: 91%. Experts: 100%.

High inter-rater-reliability
95% of assigned factors align with final version.
89% of assigned connections align with final version.

Example stories: Households

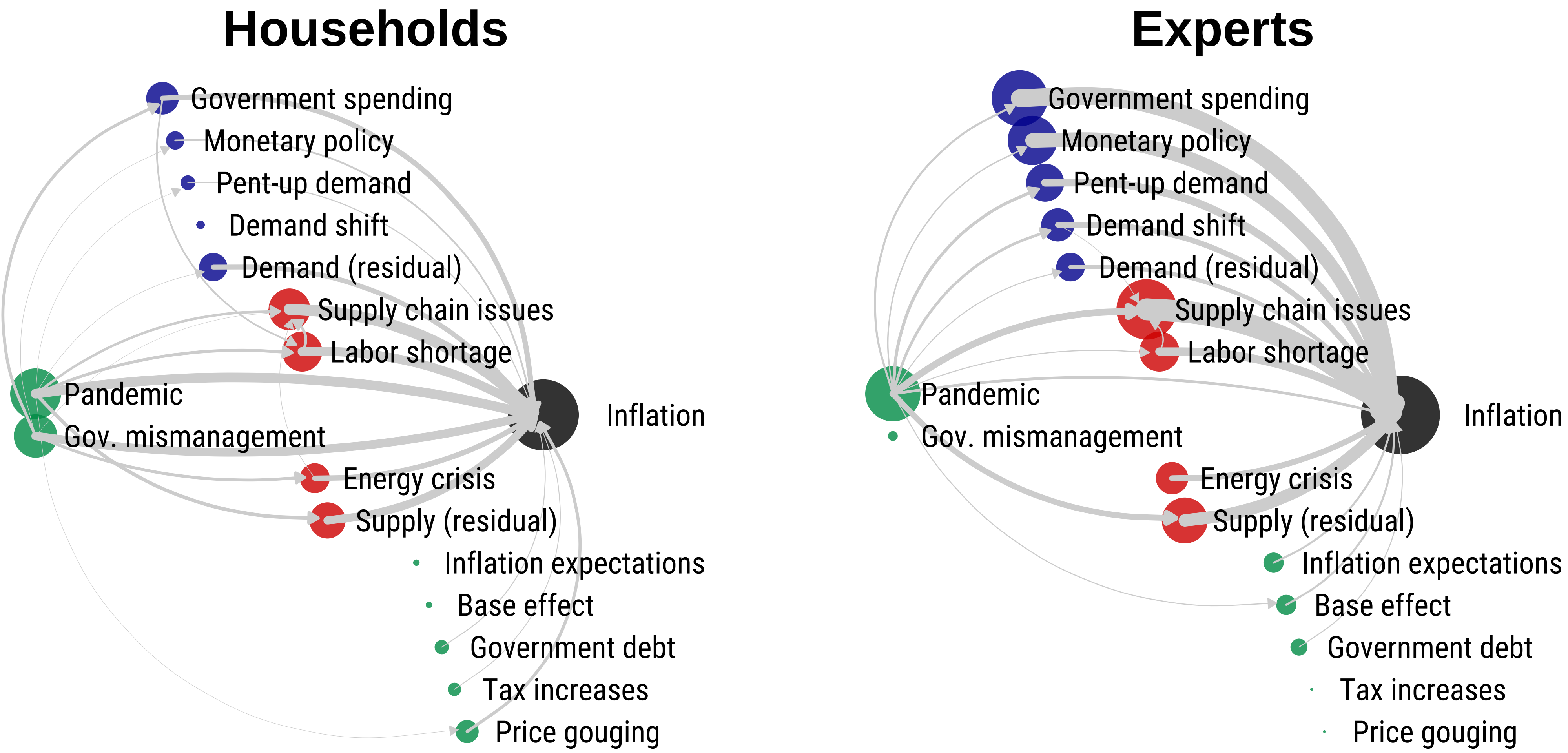
“I fully believe that our **President is responsible for this disaster** of inflation. He is not leading as he should, and people are scared. Prices are rising because of this fear. Our **President has not helped with the backflow of container ships** sitting out in the harbors. […]”





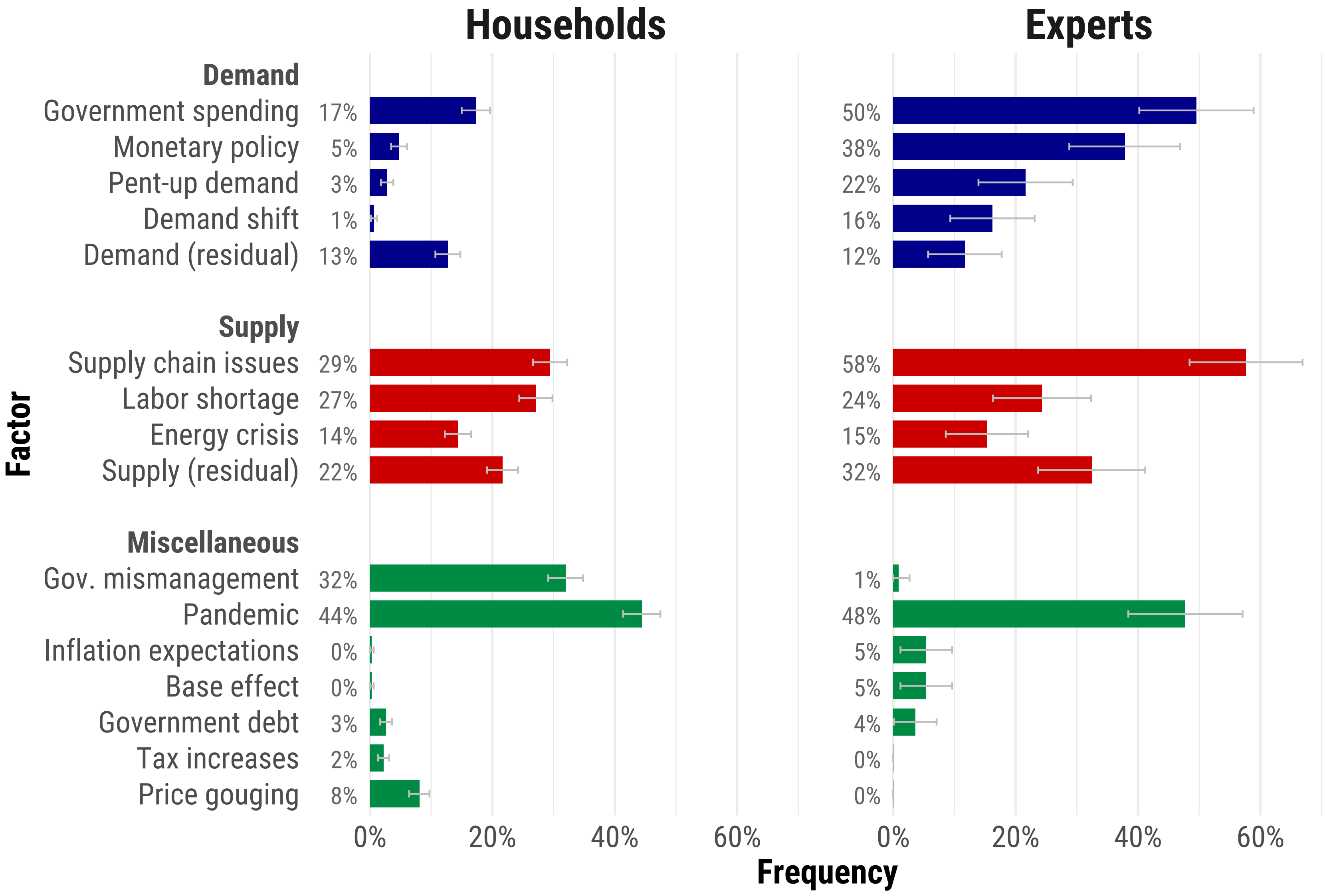
Descriptive evidence

“Average” narratives

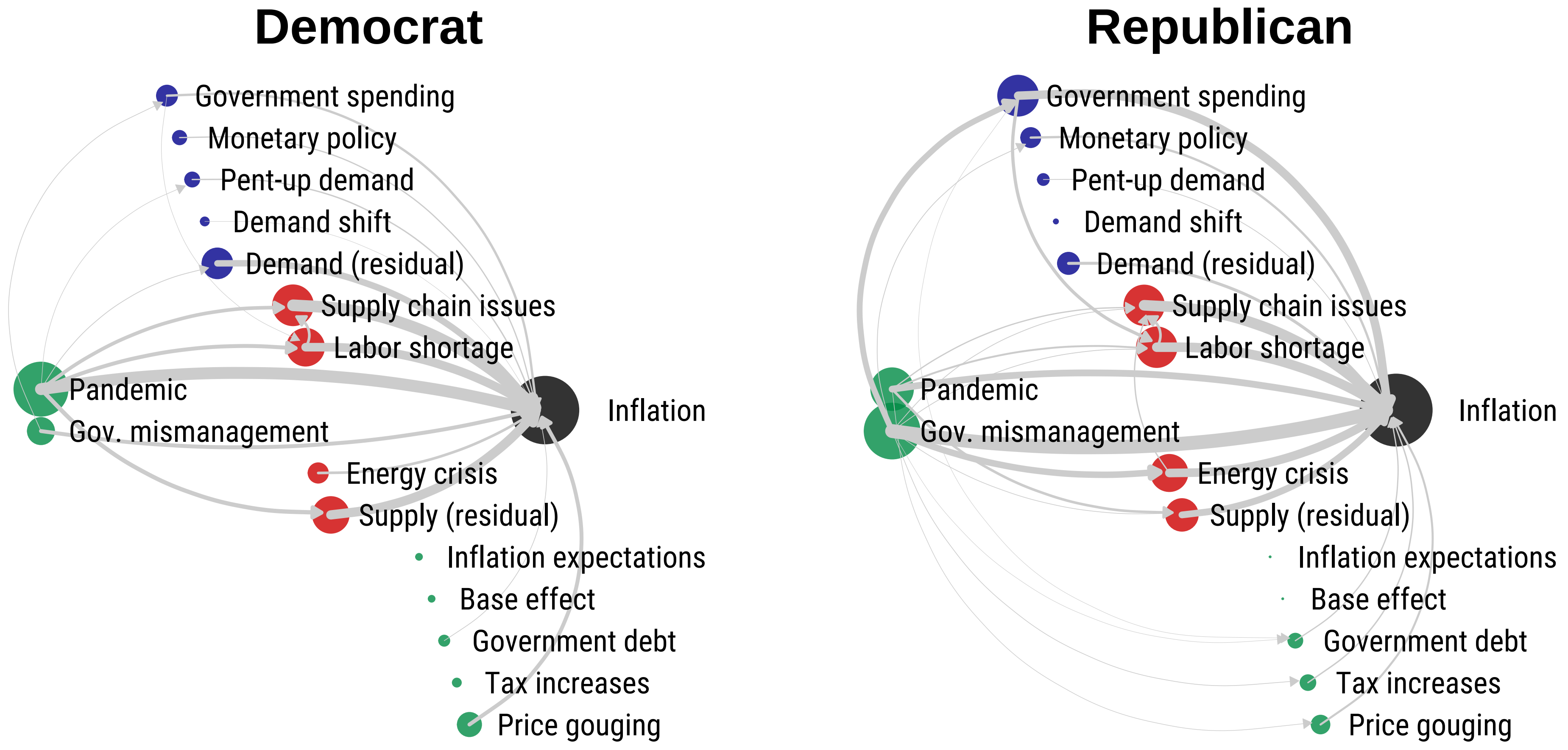


Size of nodes: frequency at which they are mentioned.
Color of nodes: blue (demand), red (supply), green (misc.), black (inflation).
Size of edges: frequency of causal link.

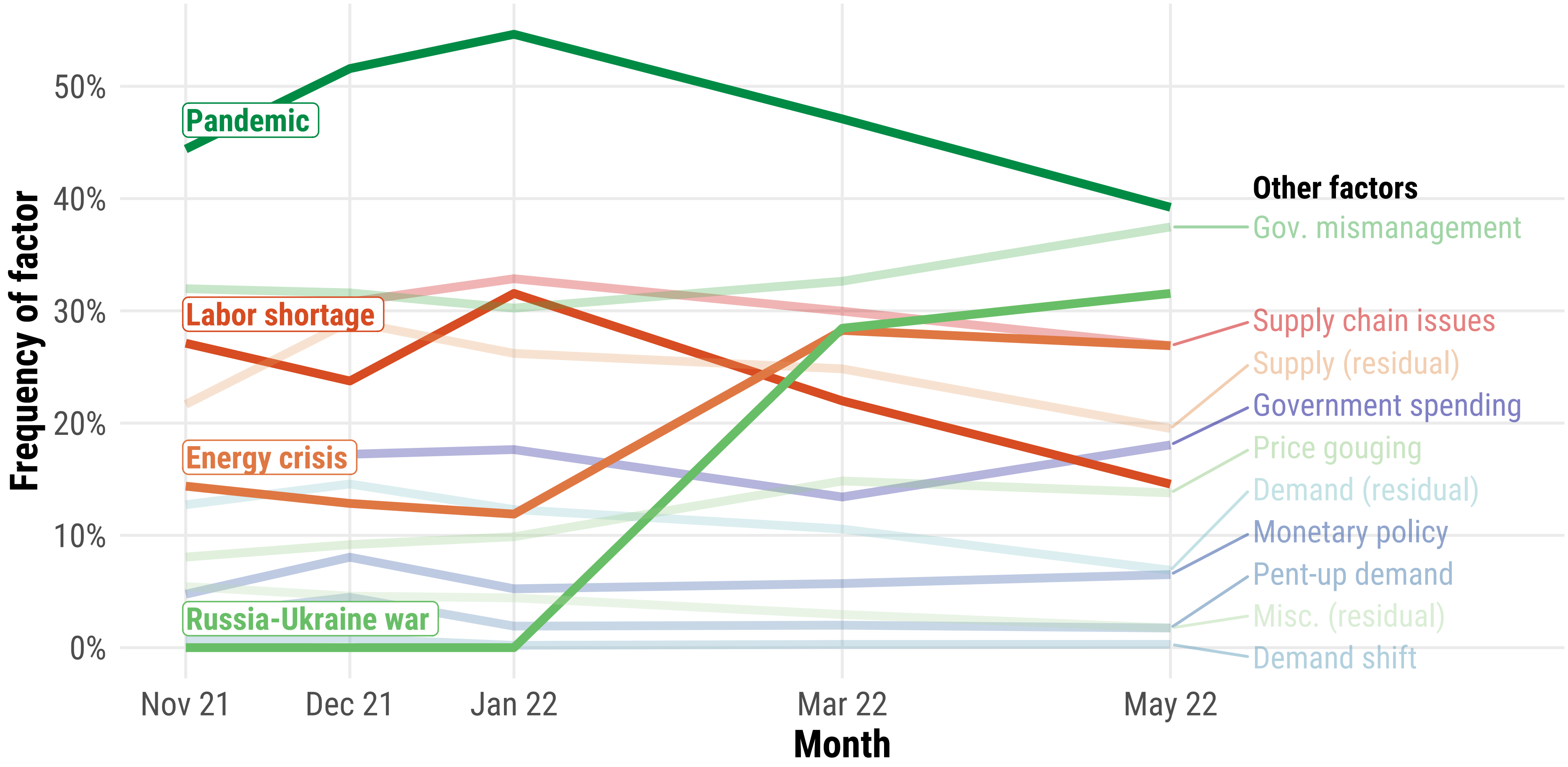
Frequency of narrative elements



Heterogeneity of narratives: Political divide



Narratives can change abruptly over time



Result 1
Descriptive evidence on narratives

Households' narratives are:

- Simpler than those of experts
- Less focused on the demand side than on the supply side
- Blame policymakers and corporations

Households endorse distinct narratives.

(Heterogeneity is strongly related to background chars.)

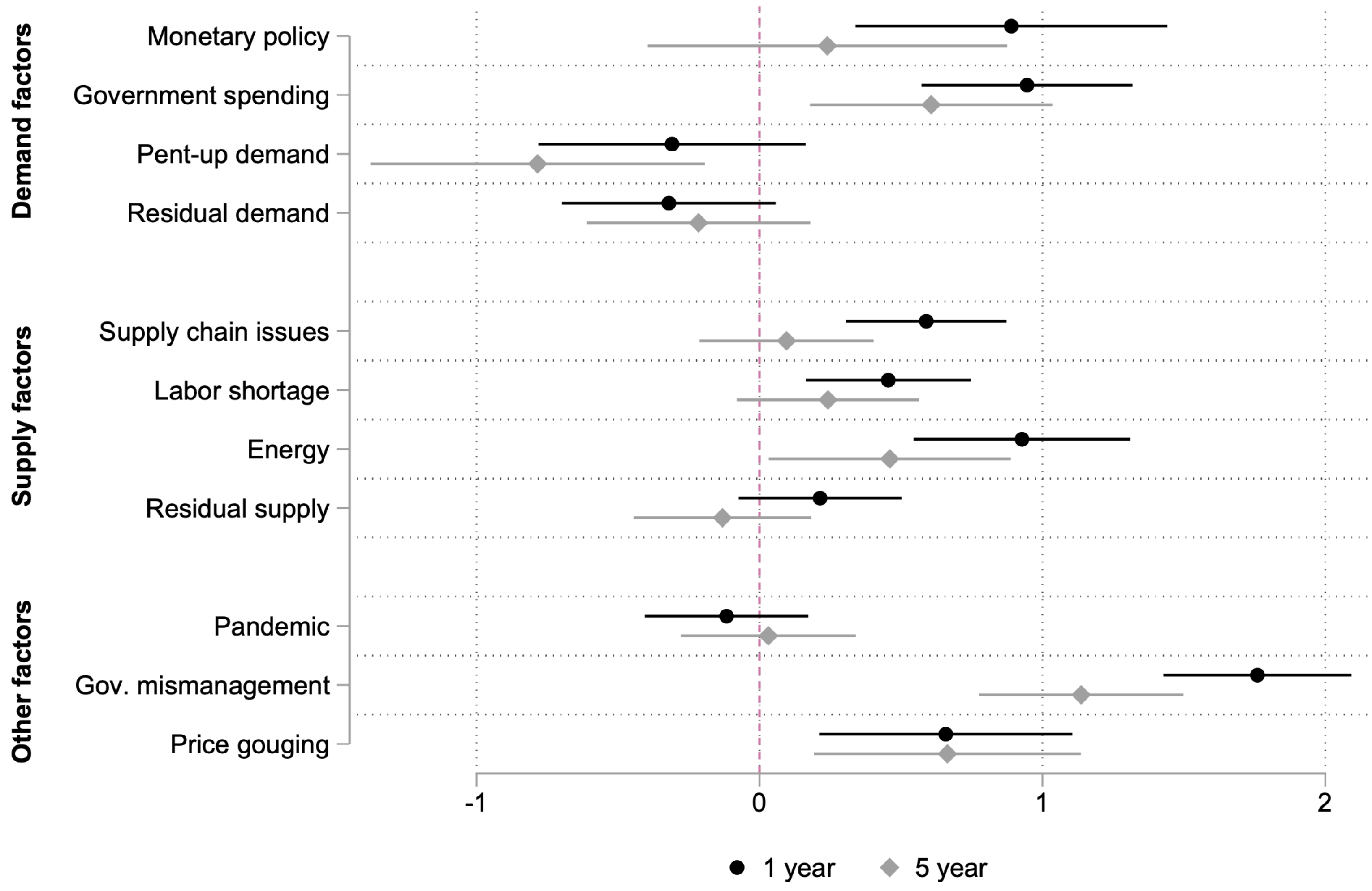
Narratives can change abruptly over time.

Narratives and expectation formation

Descriptive evidence

Narratives **strongly correlate** with inflation expectations.

Descriptive evidence



Data

Descriptive waves
Nov 21 – Jan 22
Households

Analysis

Multivariate regression

Result

Narratives are associated with different inflation expectations.

Descriptive evidence

Narratives **strongly correlate** with inflation expectations.

Experiments

Narrative provision

Provide different narratives about *past* inflation increase.

→ Affects *future* π^e.

Narrative provision: Design

Sample: Households, n = 2,398, April 2022, 2 waves, w/ Prolific.

Experimental manipulation in wave 1

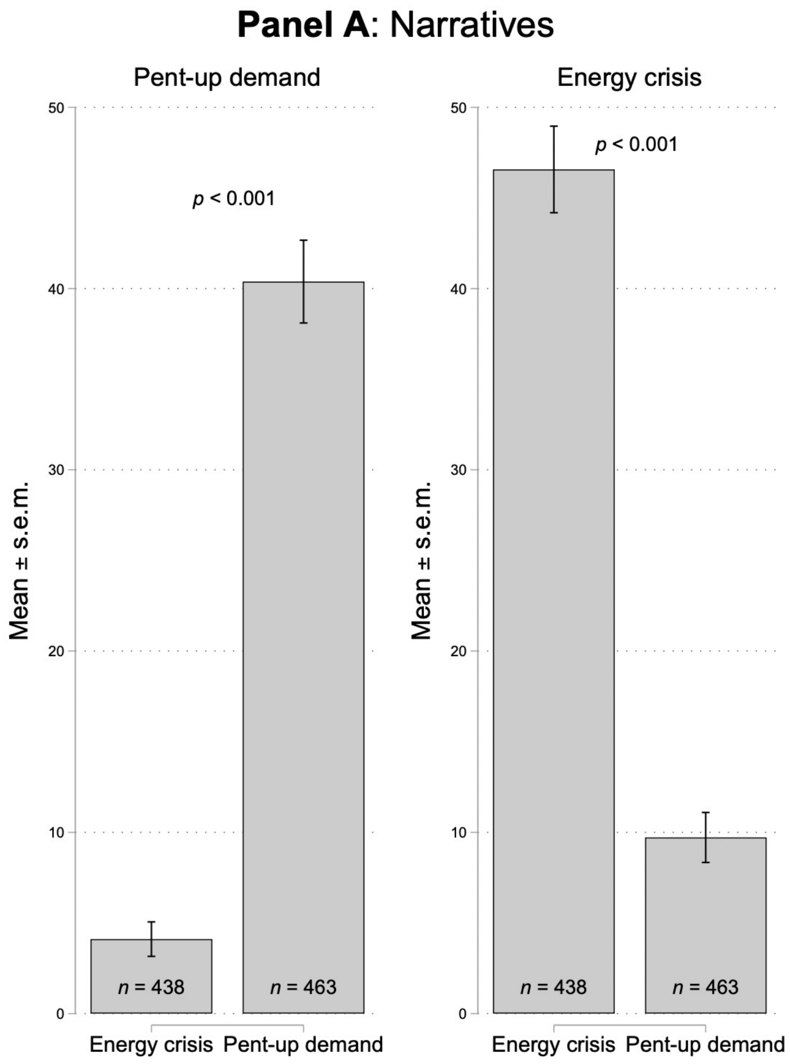
Manipulate which narratives come to mind by **providing narratives**:

- Pure control
- **Treatment 1**: Pent-up demand narrative (low persistence)
- **Treatment 2**: Energy crisis narrative (high persistence)

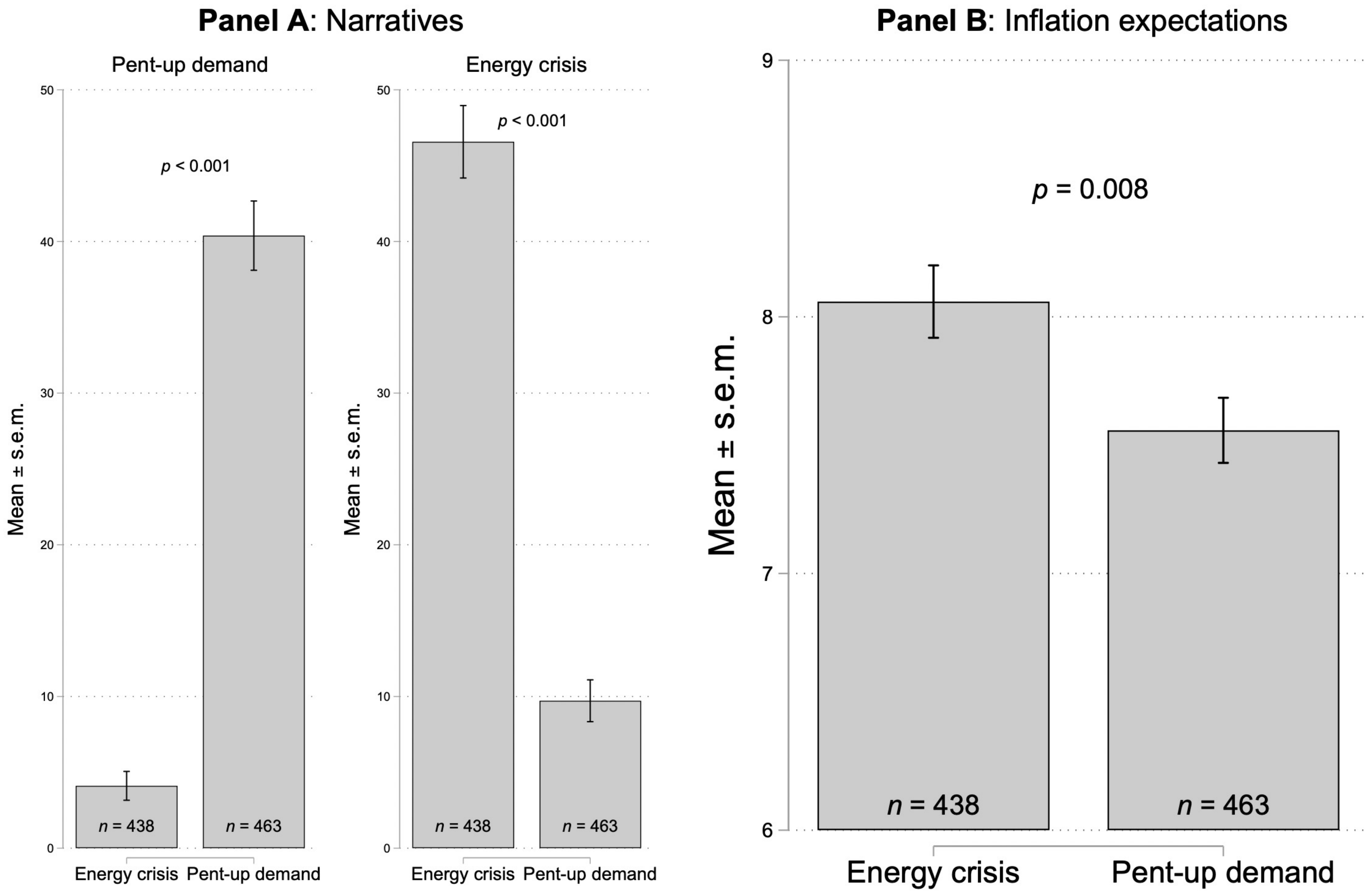
Measure inflation expectations (1y ahead).

Wave 2: Measure narratives and inflation expectations.

Narrative provision: Results



Narrative provision: Results



Descriptive evidence

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Narrative provision
Provide different narratives about *past* inflation increase.

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Provision of new information
Step 1. Provide *energy* versus *gov. spending* narrative.
Step 2. Provide experts forecast about future gov. spending.

→ Forecasts only affect π^e in gov. spending group.

Provision of new info: Design

Sample: Households, n = 997, April 2022, w/ Prolific.

2x2 factorial experimental design

1) **Provide narratives**
   - **Treatment**: Government spending narrative
   - **Active control**: Energy crisis narrative

2) **Provide info**: professional forecasts
   - High forecast (+6pp in real gov. spending)
   - Low forecast (–4pp in real gov. spending)

Then, elicit expectations.

Provision of new info: Results

	OLS	
	(1) Expected government spending growth	(2) Expected inflation rate
Panel A: Spending narrative		
Treatment: High spending		
N		
Controls		
Panel B: Energy narrative		
Treatment: High spending		
N		
Controls		
p-value: Panel A = Panel B		

Provision of new info: Results

	OLS	
	(1) Expected government spending growth	(2) Expected inflation rate
Panel A: Spending narrative		
Treatment: High spending	4.723***	
	(0.629)	
N	498	
Controls	Yes	
Panel B: Energy narrative		
Treatment: High spending	6.770***	
	(1.236)	
N	479	
Controls	Yes	
p-value: Panel A = Panel B	0.134	

Provision of new info: Results

	OLS	
	(1) Expected government spending growth	(2) Expected inflation rate
Panel A: Spending narrative		
Treatment: High spending	4.723***	1.786***
	(0.629)	(0.276)
N	498	498
Controls	Yes	Yes
Panel B: Energy narrative		
Treatment: High spending	6.770***	0.344
	(1.236)	(0.271)
N	479	479
Controls	Yes	Yes
p-value: Panel A = Panel B	0.134	0.000

Results

Both narrative groups update expected future gov. spending.

But only spending narrative group also updates inflation expectation.

Result 2
Do narratives affect expectations?

Yes, narratives about the past shape:

- how people look into the future
- how they interpret new data

Conclusion

Approach

- **Measure of narratives:** open-ended responses.
- Represented as **DAGs**.
- Apply in **descriptive surveys and experiments.**

Results

1. **Characterize nature of inflation narratives.**
2. **Narratives affect inflation expectations.**
3. **Media exposure shapes narratives.**

Implications

Heterogeneity in narratives relevant for

… understanding heterogeneity in macroeconomic expectations.

(Coibion and Gorodnichenko, 2012; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2020; Mankiw et al., 2003)

… improving expectation management and policy communication.

(Blinder et al., 2008; Coibion et al., 2019b; Haldane and McMahon, 2018; Hansen et al., 2017, 2019)

Stories, Statistics, and Memory

Thomas Graeber Chris Roth Florian Zimmermann

PhD Workshop on Subjective Beliefs, Attention and Economic Behavior
March 15, 2023

Motivation

- Widespread misperceptions shape attitudes: climate change, pandemic, inflation...
- Belief distortions puzzling where statistical info is broadly available and attended to.

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- Widespread misperceptions shape attitudes: climate change, pandemic, inflation...
- Belief distortions puzzling where statistical info is broadly available and attended to.
- This paper: **nature of human memory** may be key for understanding the persistence of misperceptions in practice.
- Anecdotal information in the form of **stories may come to mind more easily than statistics** even if unrepresentative, creating potential for systematic belief biases

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- But: may not always remember the full wealth of relevant accumulated information.
  $\rightarrow$ If so, beliefs critically hinge on **which information comes to mind**.

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Does the **type of information shape** the persistence of belief movements?

This Paper

- **Incentivized belief formation** experiments.
- Study belief formation in a setting where both statistics and stories are **natural**.
- Dynamic structure: Beliefs are elicited once **immediately** upon receiving the information and once with a **delay**.
- Systematic examination of memory mechanisms guided by a model of **cue-dependent memory**, building on Bordalo et al. (2021).

Findings

- **Story-statistic gap** in memory: effect of statistics on beliefs **decays more than twice as fast** as that of stories over the course of a day
- Key driver is more accurate **recall** of information presented as stories
- Underlying **mechanisms** - what makes information (not) stick?
  - **Contextual associations** in memory are key
  - **Features of similarity and interference** empirically most relevant for selective recall
    $\rightarrow$ lower similarity of stories to interfering information is the key driver of story-statistic gap.

Literature

- Abundance of management literature on the persuasive power of stories
  - Dozens of books and HBR articles (e.g., Fryer, 2003, Monarth, 2014, Gothelf, 2020)
  - Contribution: Focus on evolution of beliefs; uncover precise memory mechanism
- Literature on episodic memory – mostly psych (Kahana, 2012), recent work in econ
  - Theoretical (e.g., Bordalo et al., 2021, 2023) and empirical (e.g., Enke et al., 2020)
  - Contribution: Role of stories; systematic investigation of features of similarity for memory
- Emergent economic literature on role of narratives (Shiller, 2017, 2020, Michalopoulos and Xue, 2021, Andre et al., 2022)
  - Contribution: Focus on memory channel and its implications

Today

1. Baseline Design
2. The Story-Statistic Gap in Memory
   - Recall
3. Framework
4. Mechanisms
   - Contextual features
   - Features of Cross-Similarity
   - Decomposition
5. Discussion

Baseline Design

What Type of Dataset?

- Dynamic **immediate vs. delay** structure with two temporally distant but otherwise identical belief elicitations:
  - **Immediate update as benchmark for delayed belief**: captures the *perceived* informativeness of the information, both quantitative and qualitative elements.

What Type of Dataset?

- Dynamic **immediate vs. delay** structure with two temporally distant but otherwise identical belief elicitations:
  - **Immediate update as benchmark for delayed belief**: captures the *perceived* informativeness of the information, both quantitative and qualitative elements.
- **Naturalistic** belief formation setting where both statistics and stories common.
- **Incentivized** belief elicitation.
- Hold overall cognitive and memory load constant.

Experimental Design

- Subjects learn about customer reviews of 3 different (hypothetical) products/venues
  - Example: “A restaurant has received 19 reviews.”
  - Binary rating for simplicity: each review is either positive or negative

- True fraction of positive reviews uniformly drawn – induces a prior of 50%

Experimental Design

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  - Example: “A restaurant has received 19 reviews.”
  - Binary rating for simplicity: each review is either positive or negative
- True fraction of positive reviews uniformly drawn – induces a prior of 50%
- Next: subjects receive a statistic, anecdotal info or no additional info
- Task: following info, state likelihood that another, randomly selected review is positive

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?**

Statistical Information

- Statistics are defined as "a collection of information shown in numbers" (Oxford dict)
- Fraction of positive reviews for randomly selected subsample ($n > 1$) of population
- Signal randomly drawn given true number of positives $\rightarrow$ rich variation in extremity

11 of the reviews were randomly selected. **3 of the 11** selected reviews are **positive**, the others are negative.

Story

- $n = 1$, statement whether review was positive or negative overall **plus** qualitative description of review

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. ... 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!"

Key Experimental Manipulations

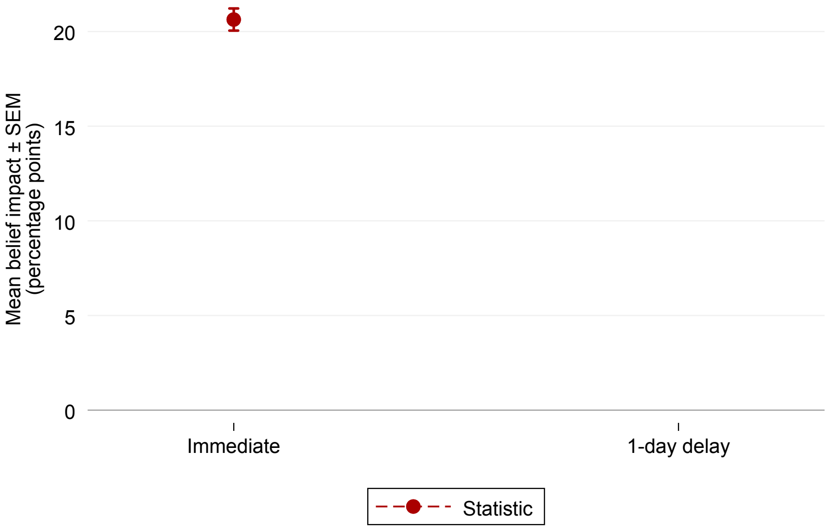
- Variation in **timing**: Beliefs are elicited twice (within-subject)
  - On the screen on which info is provided ("immediate")
  - 1 day later ("delay")
- Variation in **information** (within-subject)
  - **Type of info**: Each subject receives a statistic once, a story once and no info once.
  - **Valence of info**: each subject receives 1 positive and 1 negative piece of information.

Procedures

- Online experiments on Prolific with **large and heterogeneous samples**.
- Beliefs **incentivized** with binarized scoring rule - one (immediate or delayed) decision randomly selected to avoid hedging.
- Hypotheses and sample sizes of all studies were **pre-registered** (> 25 between-subject treatments).
- Between 250 and 500 subjects per treatment arm in final samples.

The Story-Statistic Gap in Memory

Belief Impact in Immediate and Delay



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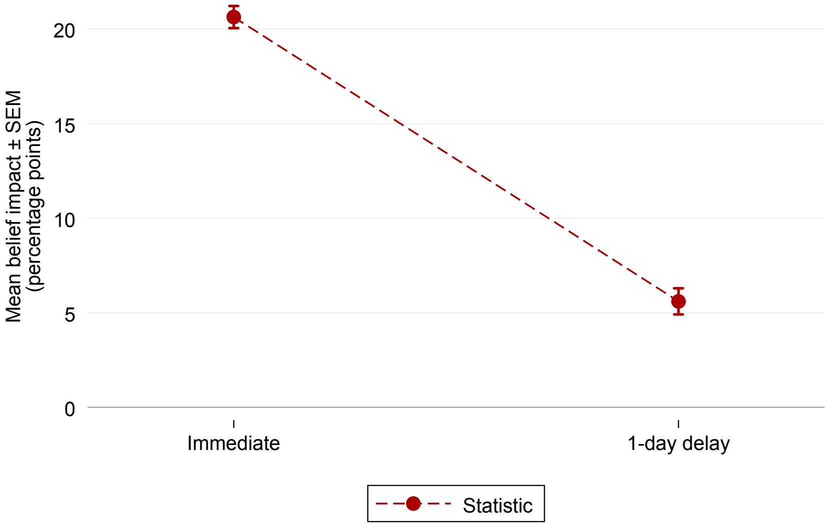

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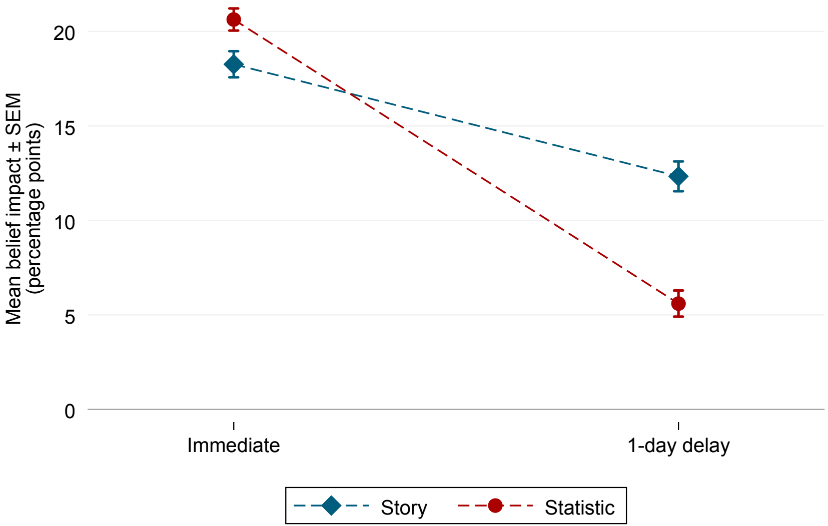

Delayed vs. Immediate Beliefs

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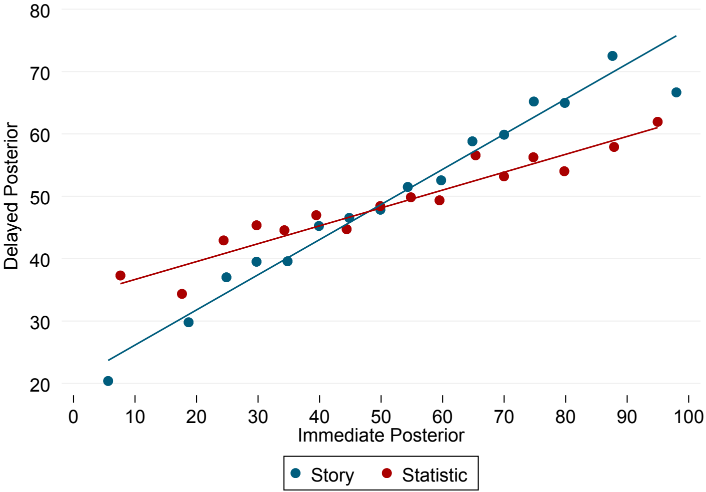

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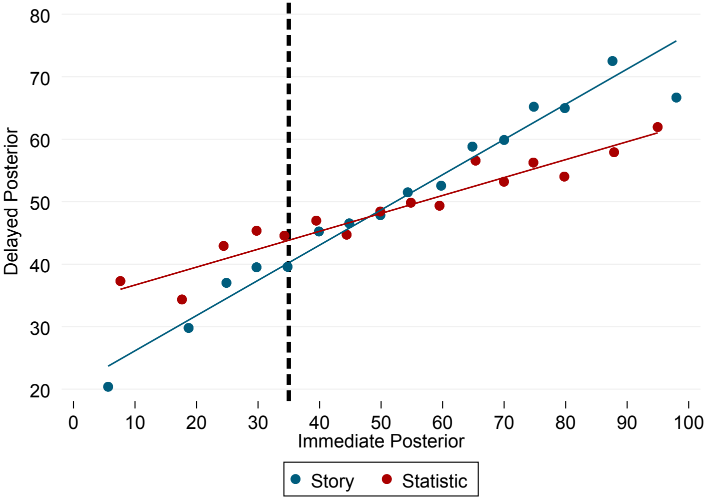

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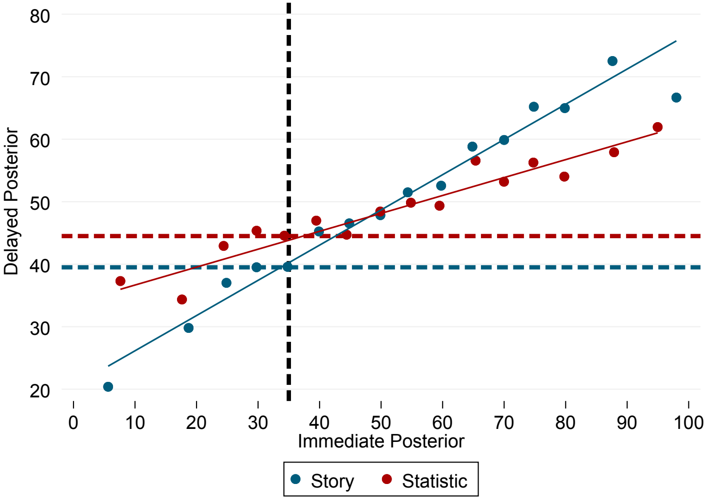

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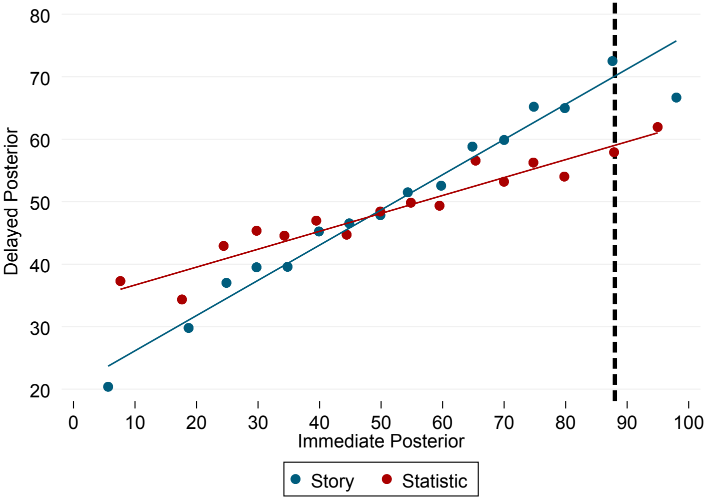

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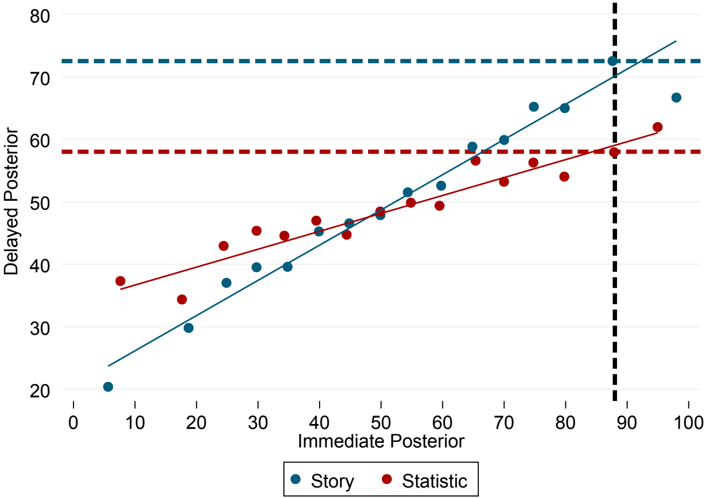

Recall

Eliciting Information Retrieval

- In baseline study, elicit memories about each scenario using unstructured **free recall**.
  - "*Please tell us anything you remember about this product scenario. Include as much detail as you can.*"
  - Rich data on recall without priming respondents on potential response categories.
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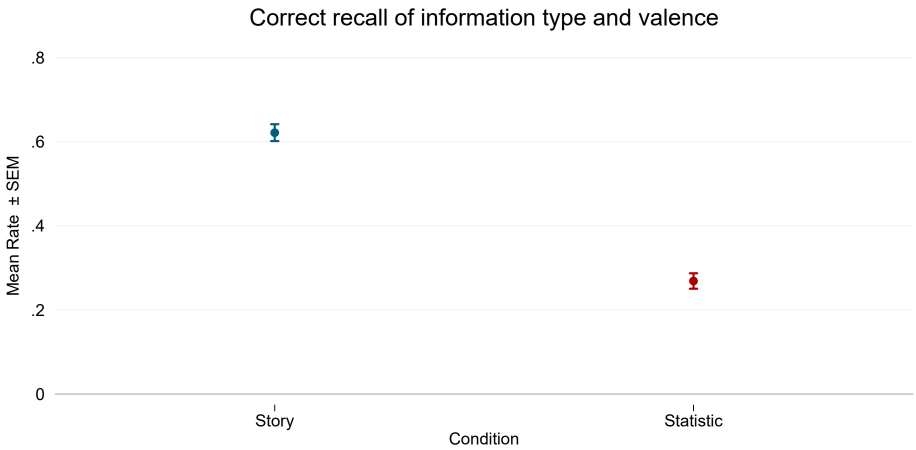
  - All responses hand-coded independently based on coding manual. High inter-rater reliability for our measure of correct recall.
- Complement with **structured, incentivized** measure in other studies.
  - We define correct recall as respondents correctly recalling the type (single review vs. multiple reviews vs. no info) and the valence of the quantitative information.
  - 5$ incentive for correct recall.

Correct Recall of Valence and Type of Information



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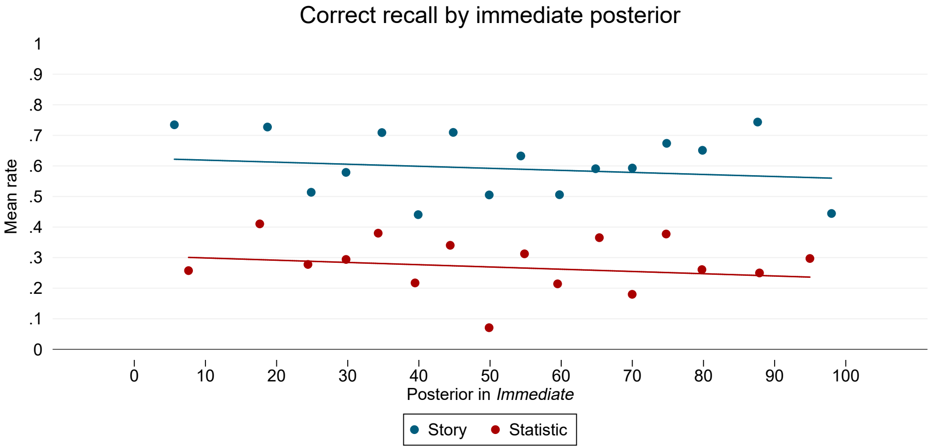

Recall Data: Taking Stock

- Main findings:
  - Substantial story-statistic gap in **correct recall** of information.
  - Independent of extremity of immediate belief updates.
- Insights from the open-ended data:
  - 44.9% mention **qualitative features** from the story.
  - Recall of own **immediate belief**: <1.3%.
  - Recall of **precise statistic**: <5%.

Robustness

- **Placebo**: Removing qualitative contextual features from the story treatment eliminates their higher recall rates.
  - Binary nature of quantitative information about a single review in story treatment is not key.
- **Robustness**: we establish robustness of baseline design to, e.g.,
  - number, type and valence of decoy information Figure
  - valence of story content Figure

Interpreting the baseline evidence

What are **potential differences between stories and statics** driving the gap?

- Engagement with information / processing time
- Prolonged processing *after* immediate belief
- Emotions / vividness (e.g., Kensinger and Schacter, 2008)

Framework

Basic setup

- Population of r_j reviews for product $j \in \{1, \ldots, I\}$, each review positive or negative
- True fraction of positives drawn independently and uniformly for each product
- In $t \in \{1, 2\}$, agent i forms belief $b^t_{i,j}$ about likelihood that random review positive

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- In $t \in \{1, 2\}$, agent i forms belief $b^t_{i,j}$ about likelihood that random review positive
- In $t = 1$, agent receives additional info about product and forms Bayesian posterior
  - Statistic consists of n_j random draws with m_j positives
  - Story consists of one randomly drawn review plus anecdotal information about review

How are beliefs in $t = 2$ formed?

The structure of memory

Adapts Bordalo et al. (2021). Memory database contains two types of memories:

- Quantitative and exact (**semantic**): with probability p, exactly recall previous belief $b^1_{i,j}$
- **Episodic** memory traces: vectors of features encoding context, quantitative information and anecdotal information

Recall of episodic memories

- Cued recall: memories retrieved upon presented with “cue” = belief prompt for product
- Agent samples once: traces in episodic memory database E **compete for retrieval**!
  - If relevant memory trace retrieved: form Bayesian update
  - If no relevant memory trace retrieved: discard sample and state prior
- Recall of episodic memory governed by **similarity** and **interference**

Similarity

- Symmetric similarity function $S(e_1, e_2) : E \times E \rightarrow [0, 1]$ between two traces:
  - Adding same feature to e_1 and e_2 increases similarity
  - Adding feature to e_1 but not e_2 decreases similarity
  - Maximum similarity of 1 if $e_1 = e_2$

Recall

- The **cued set** C contains all traces with cued product and study context switched on

Recall

- The **cued set** C contains all traces with cued product and study context switched on
- Upon being presented with cue, probability of recalling a target memory $e_0 \in C$ is:

$$r(e_0, C) = \frac{S(e_0, C)}{\sum_{e \in E} S(e, C)}$$

  - Higher **self-similarity** between target trace and cued set increases recall likelihood of e_0
  - Higher **cross-similarity** between target trace and non-cued, “irrelevant” memory traces decreases recall likelihood of e_0: interference

Stories vs. Statistics

- Generic prediction of model: Traces with **more features** exhibit **lower cross-similarity** to irrelevant traces in database, decreasing likelihood of interference
- We assume that the **anecdotal information** contained in stories create **additional features** not present in statistics traces

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- We assume that the **anecdotal information** contained in stories create **additional features** not present in statistics traces
- Baseline model: story or statistic create single trace $\rightarrow$ only cross-similarity matters

Predictions

Prediction 1. **There is a story-statistic gap in memory**: the effect of a statistic on beliefs decays more rapidly with a delay than the effect of a story.

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Prediction 2: **Adding contextual features** to a piece of info decreases belief decay.

Prediction 3: **Differences in cross-similarity** between stories and statistics drive the story-statistic gap.

Mechanisms

Contextual features

Role of Contextual Features

- Can recall of raw info be improved by merely **making up** contextual associations?
- Same setup as in baseline: 3 scenarios; one story, one statistic, once no info.

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- Can recall of raw info be improved by merely **making up** contextual associations?
- Same setup as in baseline: 3 scenarios; one story, one statistic, once no info.
- **Prompting contextualization for statistic**: Imagine how a typical review based on the provided information would look like. Please summarize your thoughts in 2 to 3 sentences.
- Between-subjects design. Note: intervention provides no additional qualitative info!

Prompting Contextualization

- Median response: 22 words (mean: 23 words)

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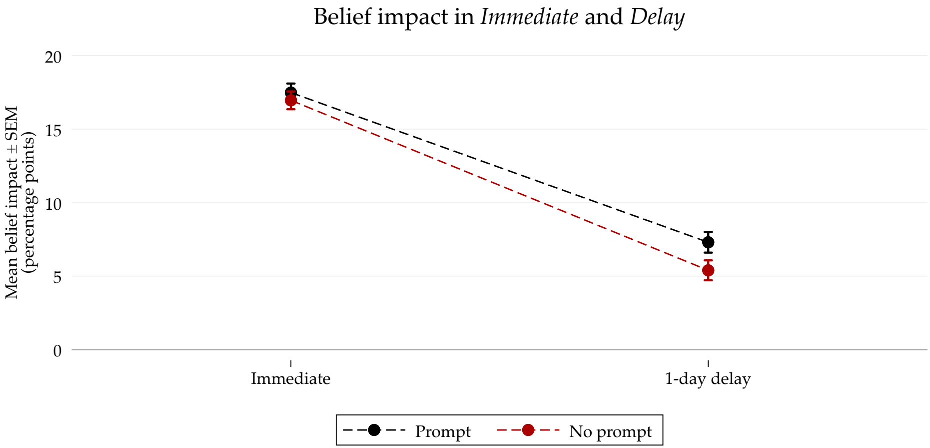
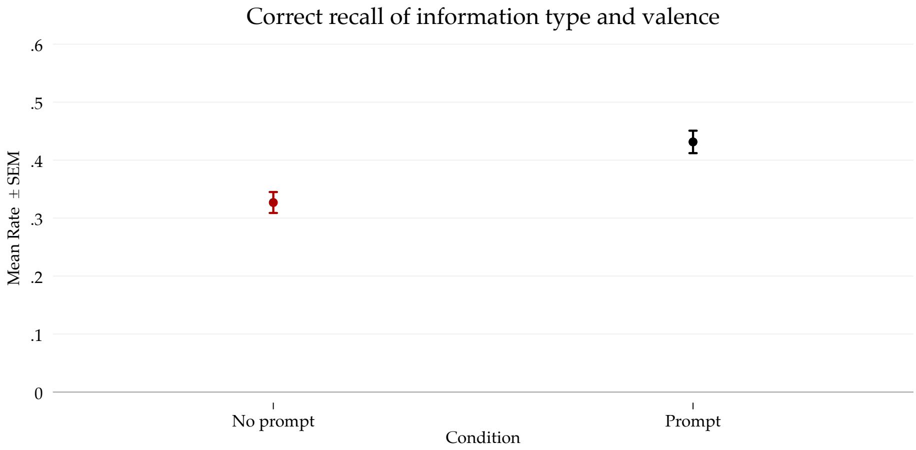
- **Example: One negative review about a video game**
  The gameplay was sub-par and glitched randomly. The graphics compared the trailer to the actual gameplay were very different giving the impression that the gameplay will have 3D style graphics while in reality, it had very old-school-style graphics. The game never mentioned that we would have to purchase additional add-ons to enjoy all the aspects of the game. This marketing sucks!

Prompting Context



Incentivized Structured Recall



Features of Cross-Similarity

Cross-Similarity

Two main experiments that test different dimensions of cross-similarity

1. Number of product scenarios
2. Similarity of different pieces of information

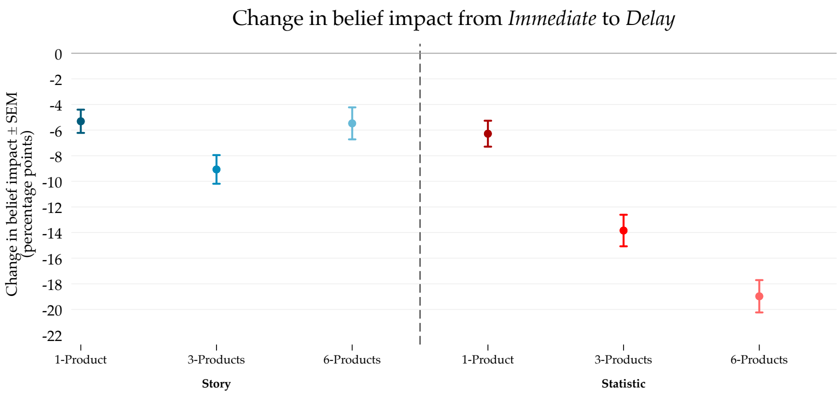
Number of product scenarios: Design

- Vary (between-subjects) whether there are 1, 3 or 6 product scenarios
  - Respondents receive 1 piece of information in the 1-product design.
  - 2 pieces of information both in the 3 and 6 product design.
- To keep incentives constant, each subject completes **six payoff-relevant tasks** in each wave: non-product-scenario tasks are dot estimation tasks.

Number of product scenarios: Prediction

- **Increases in cross-similarity** via a higher number of product scenarios tend to more strongly impede the recall of statistics than stories.
- Muted effects on stories: the richness of anecdotal content **makes stories distinctive** and hence less subject to interference from additional product scenarios.
- **Change in decoy load is constant** for story vs. statistic being the target.

Number of product scenarios

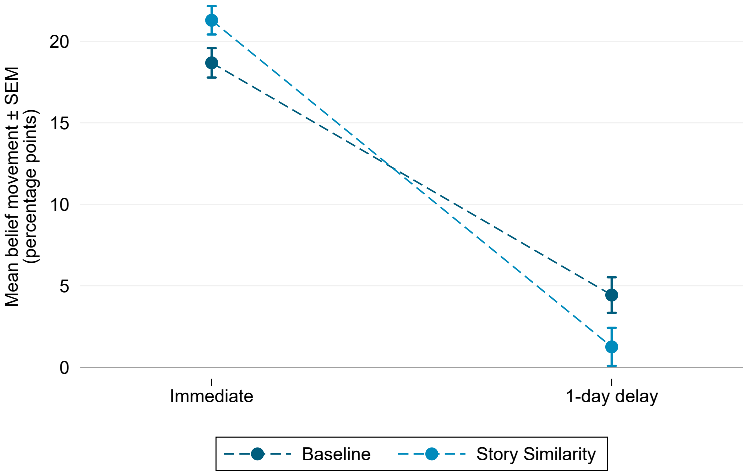


Cross-similarity of Stories

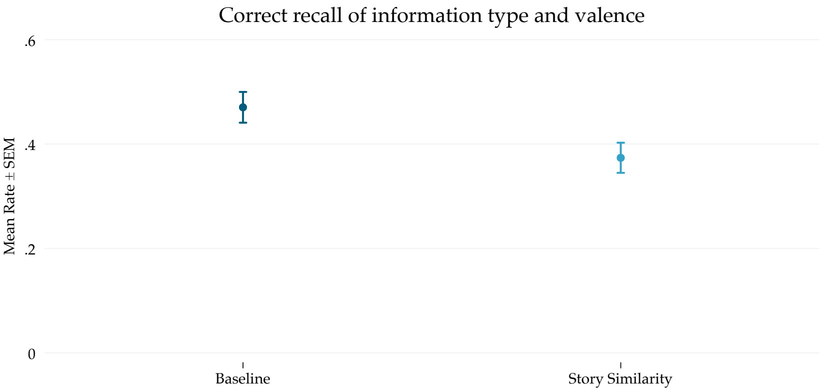
Cross-similarity of Stories

- Treatment Baseline:
  - Subjects receive a story in each of 3 scenarios: a cafe, a restaurant, and a bar
  - The 3 stories are distinct Instructions
- Treatment Story similarity:
  - Story about bar same as in Baseline
  - Other two stories are similar to the bar story (in structure and content) Instructions
- Analyze beliefs about and recall of bar scenario.
- Prediction: increase in cross-similarity decreases belief impact and recall.

Similarity of Stories: Belief Movement



Similarity of Stories: Correct Recall



Self-Similarity

- Next to cross-similarity, models of similarity and interference sometimes allow for a role of self-similarity (Bordalo et al., 2023).
  - Self-similarity measures how similar a target trace is to other target traces.
  - This plays a role when there are multiple target traces.

Self-Similarity

- Next to cross-similarity, models of similarity and interference sometimes allow for a role of self-similarity (Bordalo et al., 2023).
  - Self-similarity measures how similar a target trace is to other target traces.
  - This plays a role when there are multiple target traces.

- We conduct two mechanism experiments to gauge the importance of self-similarity.
  - In the **story-cue similarity** experiment we vary the similarity of story content to cue.
  - In the **statistic-cue similarity** experiments we vary the similarity of the statistical information and the cue by varying the format in which they are presented.

- We find relatively **weak evidence** in favor of an important role of self-similarity. Statistic-cue similarity Story-cue similarity

Decomposition

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Goal: provide approximate and tentative **quantification of the different retrieval modes**

1. Exact “semantic” recall of quantitative information or previous posterior

2. Failure to retrieve episodic memory trace (“forgetting”)

Decomposition

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1. Exact “semantic” recall of quantitative information or previous posterior
2. Failure to retrieve episodic memory trace (“forgetting”)
3. Successful recall of episodic memory trace – **possible information loss**, e.g., from gisting?

Decomposition

- Use recall data to classify full forgetting, the "**extensive margin**" of memory

  $\rightarrow$ Forgetting comprises 39% of observations in Story, but 73% in Statistic

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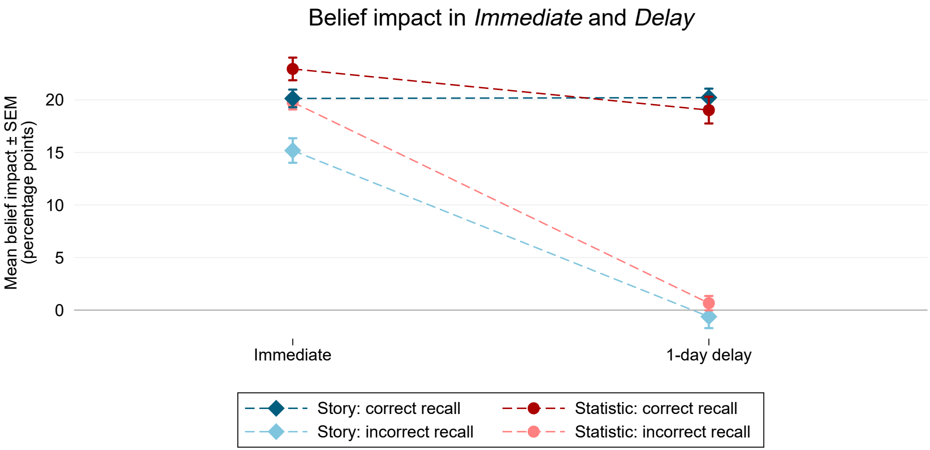
  → Identifies the "**intensive margin**" of memory loss

Belief Decay by Recall Accuracy



Decomposition

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  → Forgetting comprises 39% of observations in Story, but 73% in Statistic

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Extensive margin (retrieval failure) seems key!

Discussion

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The effect of statistics on beliefs decays at a much higher speed than that of stories.

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The effect of statistics on beliefs decays at a much higher speed than that of stories.
This pattern is shaped by the similarity-based selective recall.

- Implications for persuasively **communicating statistical information**, e.g.,:
  - Reduce cross-similarity: if know what similar info audience receives, make target different.
- **Which stories get shared** in practice? Belief distortions caused by story-statistic gap through virality of unrepresentative, extreme stories?

Implications: Mass Media

- The mass media cover many important topics (e.g. immigration, election fraud) not only by providing facts and statistics, but also relying on **anecdotes**.
- Sometimes these anecdotes stand **in contrast to official statistics**.
- For example, Ronald Reagan, beginning with his 1976 presidential 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.

Thank you

STORIES, STATISTICS, AND MEMORY

Thomas Graeber Chris Roth Florian Zimmermann

PhD Workshop on Subjective Beliefs, Attention and Economic Behavior
March 15, 2023

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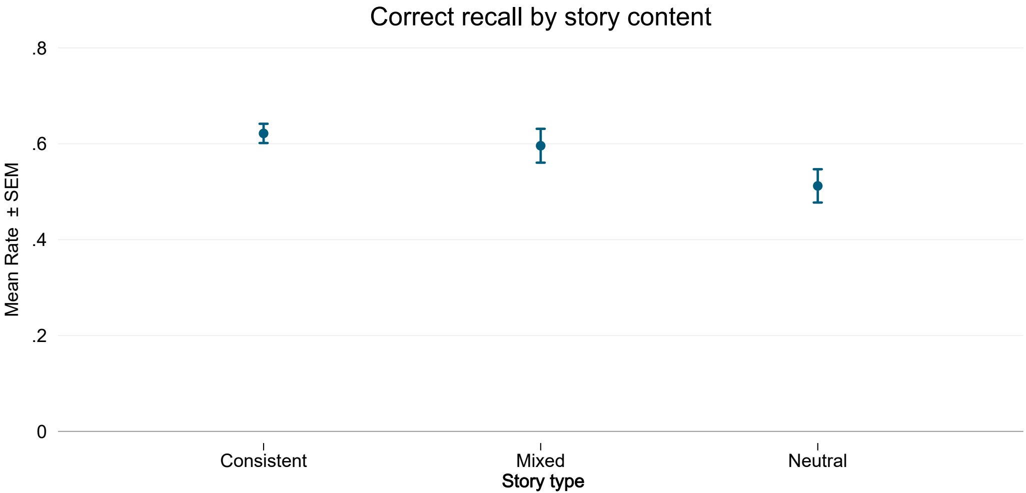
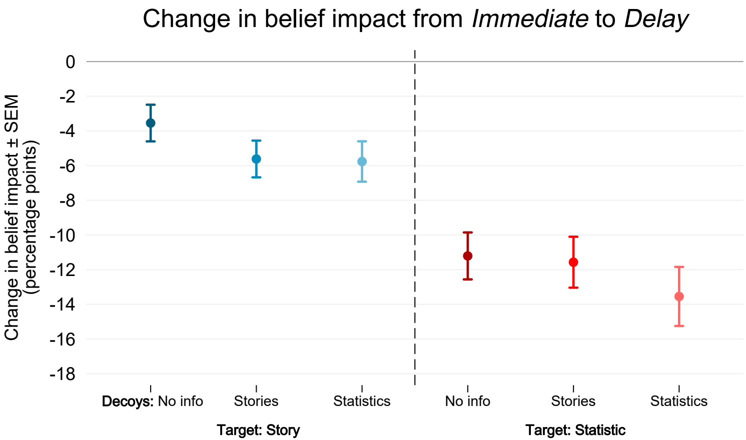
Does the Valence of Story Content Matter?



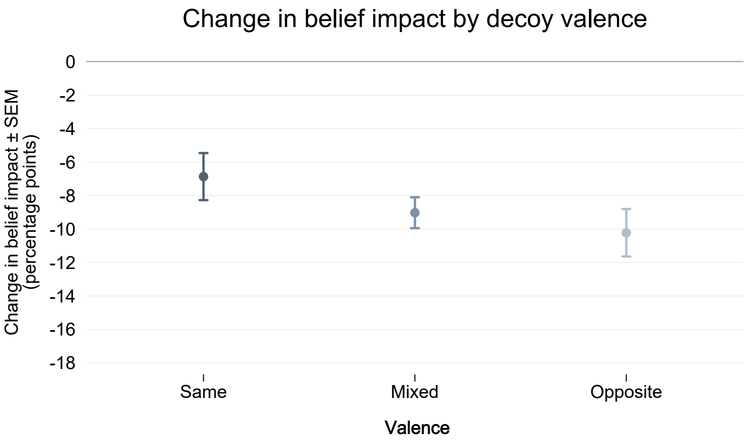
Back

Robustness to type of Decoy Information



Back

Robustness to valence of decoy Information



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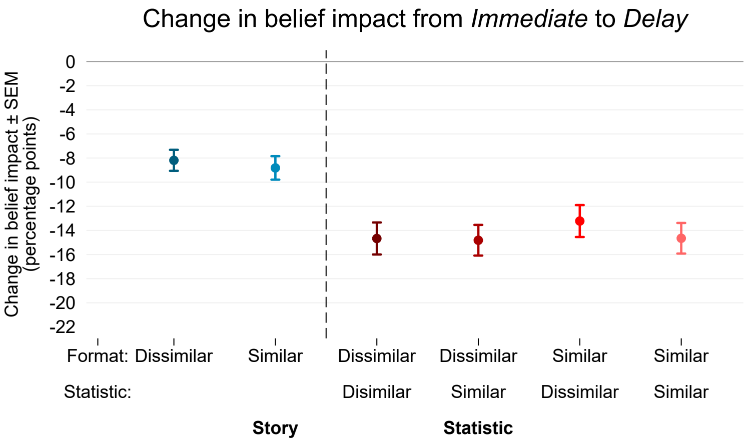
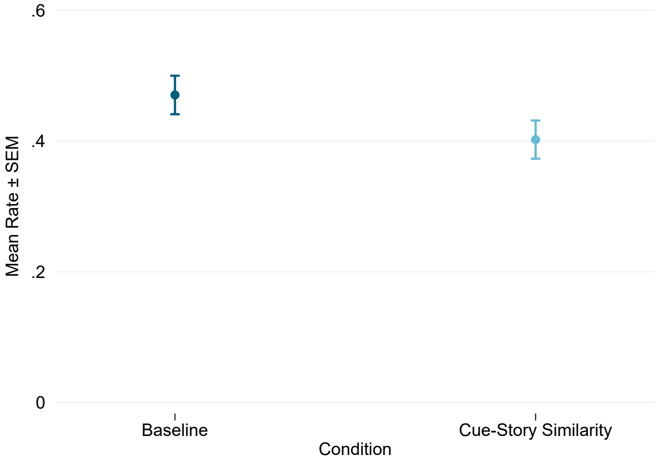
Statistic-Cue Similarity



Story-Cue Similarity



Back

Story Similarity: Baseline Condition

Bar

One of the reviews was randomly selected. The selected review is positive. It was provided by David, who most of all cares about the interior. He mentions that the interior of the place was outstanding. He describes a luxurious, spacious layout with a modern feel yet cozy atmosphere. “Entering this place will improve your mood immediately!” The second thing David really cares about is the view. According to David, the cherry on the cake is a breath-taking view from this rooftop location on the 51st floor. A majestic look over the entire city completes this phenomenal place that David describes as offering the “best overall vibe of the city”. Back

Story Similarity: Baseline Condition

Restaurant

One of the reviews was randomly selected. The selected review is negative. It was provided by Justin, who most of all cares about the quality of the food. 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. The second thing Justin really cares about is how authentic the food is. Justin was disappointed by the Western taste that was very different from what he remembered from his holiday in Japan. As they left the restaurant, Justin was very annoyed and thought to himself “I definitely won’t be back!” Back

Story Similarity: Baseline Condition

Cafe

One of the reviews was randomly selected. The selected review is negative. It was provided by Linda, who most of all cares about the service quality. She complained that the service quality was incredibly poor. Nobody initially showed her to a table so she stood in the entrance for a full 10 minutes. Even though there were few customers, the waiters all seemed stressed and were rude to her. The waiter spilled hot coffee over Linda's pants. The second thing Linda really cares about are waiting times. Because the waiter brought the wrong food, Linda had to wait another half hour. The waiter did not apologize. Linda describes the service in the cafe as the disappointment of a lifetime and was fuming with rage as she left the cafe.

Back

Story Similarity: Treatment Condition

Restaurant

One of the reviews was randomly selected. The selected review is negative. It was provided by Justin, who most of all cares about the interior. He mentions that the interior of the place was poor. He describes a worn-down, claustrophobic space with an outdated feel and depressing atmosphere. “Entering this place will kill your mood immediately!” The second thing Justin really cares about is the view. According to Justin, what adds insult to injury is the practically non-existent view from this basement location. The lack of daylight completes this disappointing place that Justin describes as the “worst vibe you can possibly get in this city”.

Back

Story Similarity: Treatment Condition

Cafe

One of the reviews was randomly selected. The selected review is negative. It was provided by Linda, who most of all cares about the interior. She mentions that the interior of the place was disappointing. She mentions a time-worn, carelessly put together furnishing that did not look clean and was slightly smelly. “Coming here will make you want to leave immediately!” The second thing Linda really cares about is the view. According to Linda, what made matters worse is the absence of any windows and the glaring fluorescent lighting. The absence of natural light completes this frustrating venue that Linda describes as the “most dismal vibe in the area”. Back