News Media and Delegated Information Choice

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The man who buys a newspaper does not know beforehand what will be in the news.

Jacob Marschak, 1960

Public Information and Coordination

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But what do we mean when we say that information is *public*?

Public Information and Common Knowledge

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We ask: How do editorial decisions affect the degree to which information about specific events is common knowledge?

The Plan and a Quick Preview

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- Analyze how the editorial function of news media affect agents beliefs and actions

Measuring News Coverage

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Main Advantages:

- Objective and the results can be replicated
- Naturally measures the relative importance of topics

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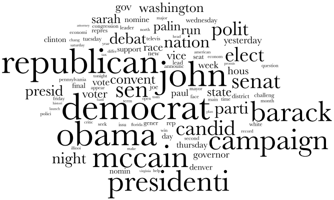
The number of topics is set to 10 in our benchmark specification

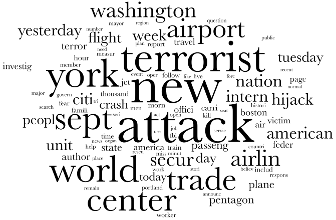
Newspaper Sources

Newspaper Full Name	Short Name	Newspaper Full Name	Short Name
Atlanta Journal	AJ	The Las Vegas Review-Journal	LVR
Charleston Gazette	CG	The New York Times	NYT
Pittsburgh Post-Gazette	PPG	The Pantagraph	PG
Portland Press Herald	PPH	The Philadelphia Inquirer	PI
Sarasota Herald-Tribune	SHT	The Wall Street Journal	WSJ
St. Louis Post-Dispatch	SLP	The Washington Post	WP
Telegram & Gazette Worcester	TGW	USA Today	UT
The Boston Globe	BG	Winston-Salem Journal	WiSJ
The Evansville Courier	EC		

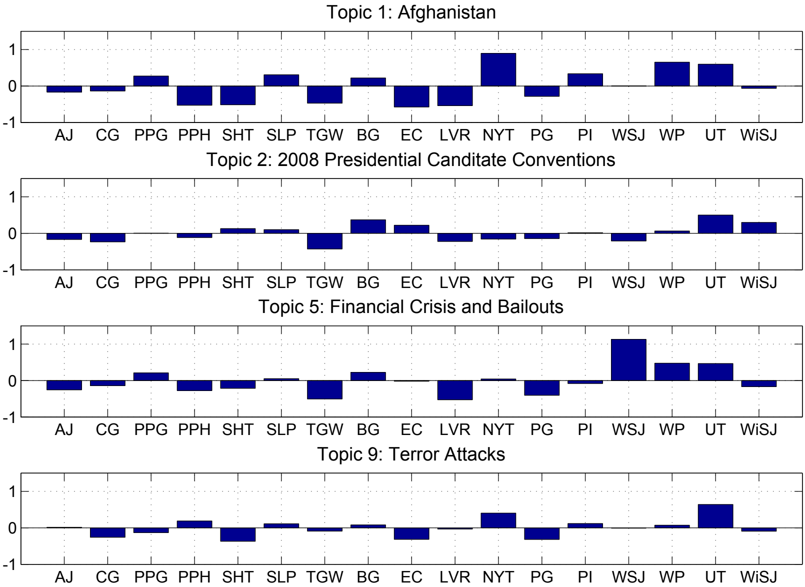
The Estimated News Topics

Topics 1,2,5 and 9 as Word Clouds





Specialization of Newspapers



Two Measures of News Coverage over Time

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1. **Fraction of total news** devoted to topic k on day t

$$F_{t,k} \equiv \frac{\sum_d \theta_{t,d,k}}{D_t}$$

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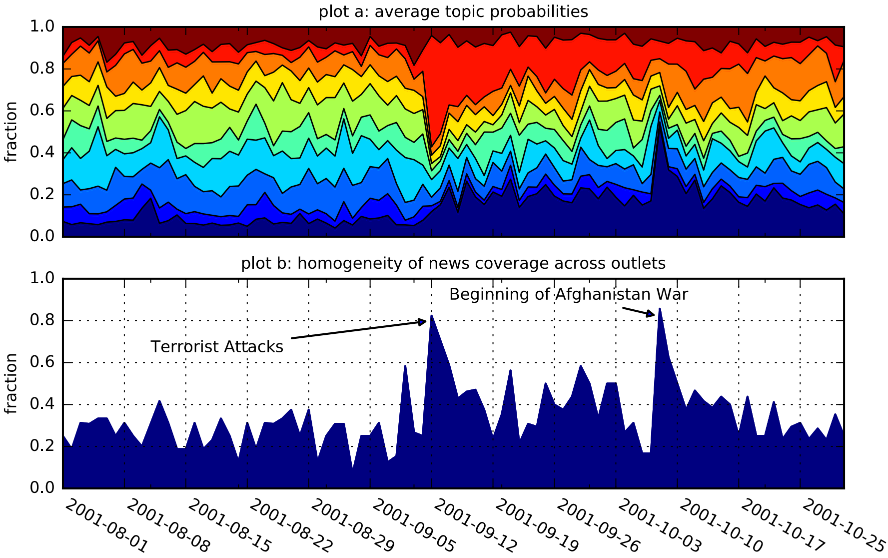
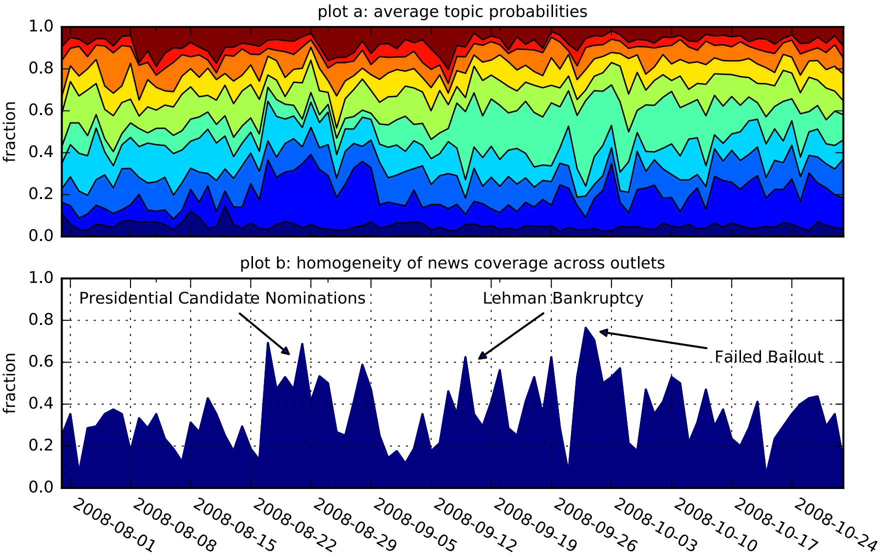
2. **Homogeneity** of news coverage

$$H_t \equiv \frac{\sum_m \mathcal{I}\left(\arg\max_k F_{t,m,k} = \arg\max_k F_{t,k}\right)}{M}$$

Editorial Decisions around 9/11



Editorial Decisions around Lehman Bankruptcy



A Beauty Contest Model with News Media and Delegated Information Choice

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1. Agents have heterogeneous interests
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The model incorporates these features in as simple of a setup as possible

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- $\mathcal{S}_i = 1$ means that Paper i reports X_i

Simple Discrete State Space Example

The Model with a Discrete State Space

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Neither the symmetry nor the independence of the distributions for X_a and X_b are necessary

Equilibrium News Selection Functions

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No strategic motive

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Paper A

	$X_a = -1$	$X_a = 0$	$X_a = 1$
$X_b = -1$	A	A	A
$X_b = 0$	A	A	A
$X_b = 1$	A	A	A

Paper B

	$X_a = -1$	$X_a = 0$	$X_a = 1$
$X_b = -1$	B	B	B
$X_b = 0$	B	B	B
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Strategic motive ($\lambda \neq 0$)

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News selection function

Strategic motive $(\lambda \neq 0)$

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Consider the state $(0, 1)$:

- Alice knows that $X_b = 1$
- But she also knows that $X_a = 0$, since in the states $(1, 1)$ and $(-1, 1)$ she would observe X_a

News selection function

Strategic motive $(\lambda \neq 0)$

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News Selection Functions and Higher Order Beliefs

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Consider the state $(1, 0)$:

News selection function

Strategic motive $(\lambda \neq 0)$

Paper A

	$X_a = -1$	$X_a = 0$	$X_a = 1$
$X_b = -1$	A	B	A
$X_b = 0$	A	A	A
$X_b = 1$	A	B	A

Paper B

	$X_a = -1$	$X_a = 0$	$X_a = 1$
$X_b = -1$	B	B	B
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- Both Alice and Bob know that $X_a = 1$

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Consider the state $(1, 0)$:

- Both Alice and Bob know that $X_a = 1$
- Bob can infer with certainty that Alice also knows that $X_a = 1$
- Alice assigns probability $\frac{1}{2}$ to Bob knowing that $X_a = 1$

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Actions and Common Information

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Alice's action when she observes X_a

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$$y_a(x_a) = (1-\lambda)\, x_a + \lambda p\,(S_b = 0 \mid S_a = 1, x_a)\, y_b(x_a)$$

Actions and Common Information

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$$y_a(x_a) = \frac{(1-\lambda)}{1-\frac{1}{2}\lambda^2}x_a, \qquad y_b(x_a) = \lambda\frac{(1-\lambda)}{1-\frac{1}{2}\lambda^2}x_a$$

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The strength of the response of both agents depends on $p(S_b = 0 \mid S_a = 1, x_a)$.

Additional Results in Paper

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Delegated information choice introduces correlation in actions compared to ex ante signal choice model

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Continuous distributions

- Extreme events are closer to common knowledge
- The degree to which information about a given event is common depends on preferences and distributions

Conclusions

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We made strong assumptions regarding benevolence of news media

- Report events with perfect accuracy and select to maximize utility of readers
- As long as news selection is systematic and understood by the agents, the mechanism applies

Appendix

News Selection Functions and Beliefs

Proposition: Posterior beliefs about the unreported story X_j coincides with the prior distribution $p(x_j)$, i.e.

$$p(x_j \mid \mathcal{S}_i = 1, x_i) = p(x_j) \tag{1}$$

only if the probability of reporting x_i is conditionally independent of x_j

$$p(\mathcal{S}_i = 1 \mid x_i) = p(\mathcal{S}_i = 1 \mid x_j, x_i).$$

Proof: By Bayes' rule

$$p(x_j \mid \mathcal{S}_i = 1, x_i) = \frac{p(\mathcal{S}_i = 1 \mid x_j, x_i)}{p(\mathcal{S}_i = 1 \mid x_i)} p(x_j)$$

so that (1) holds only if

$$\frac{p(\mathcal{S}_i = 1 \mid x_j, x_i)}{p(\mathcal{S}_i = 1 \mid x_i)} = 1.$$

Delegated News Selection and Correlated Actions

Alternative Benchmark Model: Optimal Actions with Ex Ante Signal Choice

Agents subject to same constraint on number of stories but must choose *ex ante* which story to read about.

When $\left(1-\lambda^2\right)^2+\lambda>0$

- Alice will choose to always observe X_a
- Bob will choose to always observe X_b.

Since

$$E\left[x_i \mid x_j\right]=0 : i \neq j$$

the optimal action is given by

$$y_i=(1-\lambda)\,x_i : i \in a, b$$

Alice and Bob's actions are uncorrelated if X_a and X_b are independent

News Selection and Correlation of Actions

Direct computation of the correlation of Alice and Bob's actions gives

$$\frac{\sum p(\omega)\, y_a(\omega) y_b(\omega)}{\sqrt{var(y_a)}\sqrt{var(y_b)}} = 2\lambda \frac{(1-\lambda)^2}{(2-\lambda^2)^2} var(y_i)^{-1}$$

- The terms in the sum associated with the states $(0,1), (0,-1), (1,0)$ and $(-1,0)$ have the same sign as λ with delegated news selection
- The same terms are zero with ex ante information choice

Extreme Events

Extreme Events and Approximate Common Knowledge

The discrete, low dimensional set up does not lend itself to study large magnitude, or extreme, events

Continuous distributions of events allow us to think of how the magnitude of an event affect beliefs and actions

- $X_i \sim N(0, \frac{1}{3})$
- News selection parameterized a

$$\mathcal{S}_i = \begin{cases} 1 \text{ if } |x_i| \geq \alpha |x_j|^{\beta} \\ 0 \text{ otherwise} \end{cases}$$

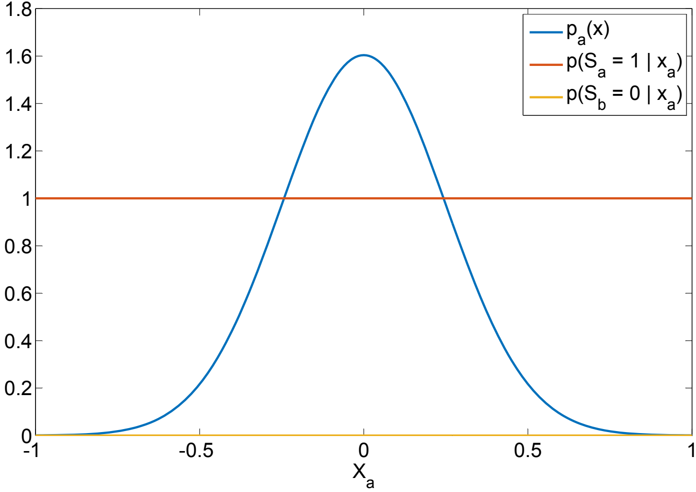
- Optimal actions

$$y_i(x_i) = \frac{(1-\lambda)}{1-\lambda^2 p(\mathcal{S}_j = 0 \mid x_i, \mathcal{S}_i = 1)} x_i$$

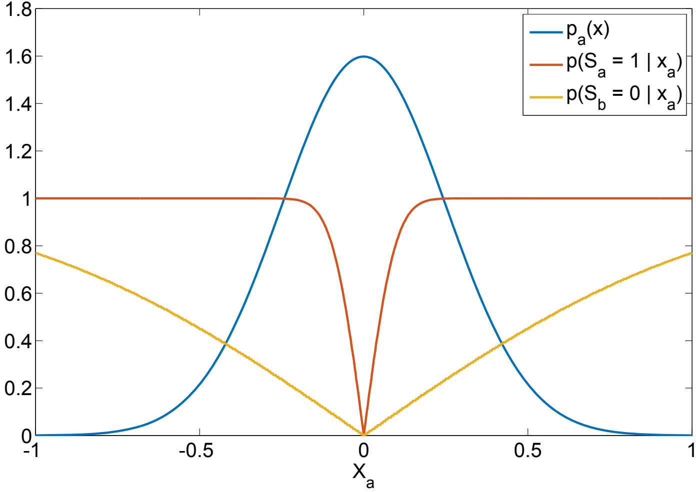
and

$$y_i(x_j) = \lambda \frac{(1-\lambda)}{1-\lambda^2 p(\mathcal{S}_i = 0 \mid x_j, \mathcal{S}_j = 1)} x_j$$

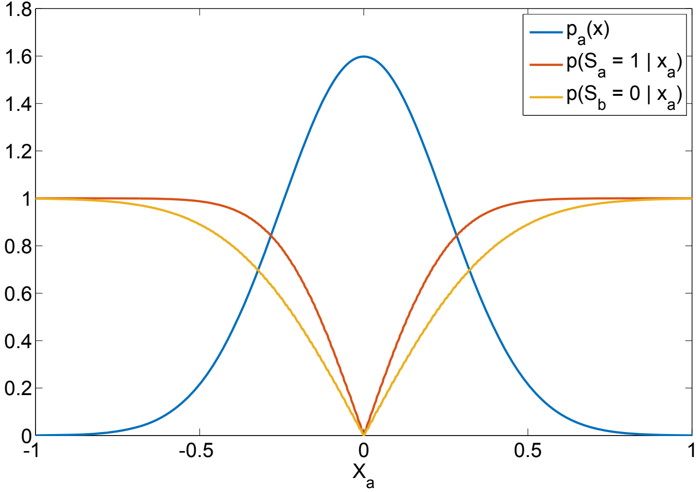
Extreme Events and Common Knowledge
$\lambda = 0$



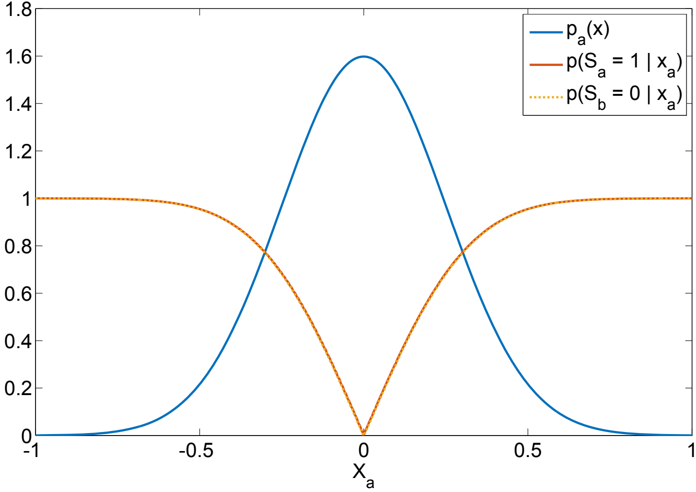
Extreme Events and Common Knowledge
$\lambda = 0.3$



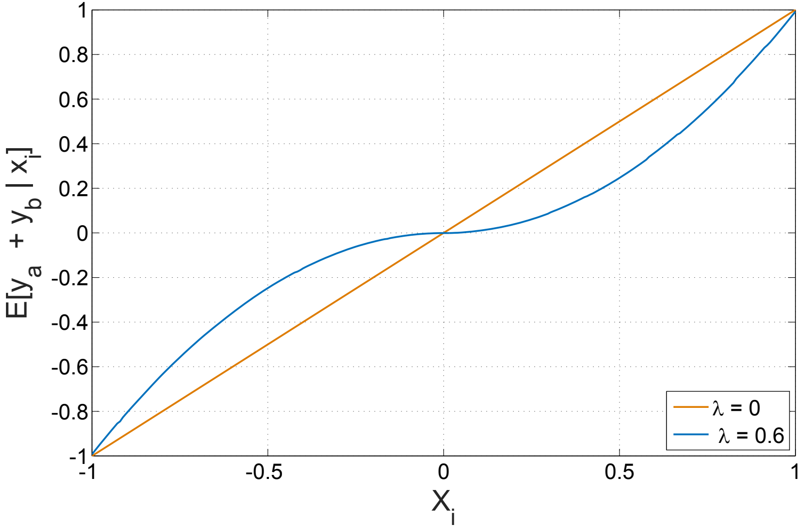
Extreme events and common knowledge $\lambda = 0.45$



Extreme Events and Common Knowledge
$\lambda = 0.6$



Expected Aggregate Action



Estimating the LDA Model

The probability of a specific text corpus being generated is described by the distribution

$$p(\beta, \theta, z, w) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n} \mid \theta_d)\, p(w_{d,n} \mid \beta_{1:K}, z_{d,n}) \right)$$

where β, θ and z are unobserved parameters and w is a vector space representation of the text corpus.

We want to form a posterior distribution for the latent parameters conditional on the observed text corpus

$$p(\beta, \theta, z \mid w) = \frac{p(\beta, \theta, z, w)}{p(w)}$$

We use Collapsed Gibbs Sampling algorithm of Griffiths and Steyvers (2004)