DELEGATED INFORMATION CHOICE

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ABSTRACT. News media provide an editorial service for their audiences by monitoring a large number of events and by selecting the most newsworthy of these to report. Using a Latent Dirichlet Allocation topic model to classify news articles, we document the editorial function of US newspapers. We find that, while different newspapers on average tend to emphasize different topics, news coverage becomes more homogenous across newspapers after major events. We propose a theoretical model that can match these facts. In the model, agents delegate the choice of what to get information about to specialized providers that condition on ex post outcomes before deciding what to report. Because what different information providers choose to report is state dependent, the degree to which information about a given event is common among agents is endogenous and depends both on agents' preferences and the distribution of possible events. If agents have a strategic motive, they respond more strongly to events that they can infer are closer to common knowledge. Because different providers in some states of the world choose to report the same event, agents' actions are more correlated compared to a model in which agents choose ex ante what to get information about.

1. INTRODUCTION

Every day, a very large number of events occur, each of them potentially relevant for the decisions of firms and households. However, no individual firm or household has the resources to observe all of these events. Instead, many rely on news media to monitor the world on their behalf. One important function that news media perform is thus editorial. Among all potential stories that occur, only those that are deemed most newsworthy are reported. In this paper, we analyze how this type of delegation of agents' information choice to specialized providers affects the beliefs and strategic interaction of economic agents.

Strategic decisions based on imperfect information are pervasive in economics. For example, producers in oligopolistic markets need to predict the output of their competitors, speculators need to predict whether other speculators plan to attack a currency, and price setters need to predict the pricing decisions of other firms. In such settings, it is well known that public signals are disproportionately influential as they are particularly useful for agents that need to predict the actions of other agents, e.g. Morris and Shin (2002).

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Arguably, everything that is reported by news media is public in the sense that it is available to those who care to read it. However, in reality, not all of this information is common knowledge. That is, not all information that is publicly available is also observed by everybody, and not all information that *is* observed by everybody is also *known* to be observed by everybody, and so on. In this paper, we argue that understanding the editorial role played by news media is central to understanding the degree to which knowledge about an event is common among agents.

We begin by estimating a Latent Dirichlet Allocation (LDA) topic model based on texts from almost 15,000 archived newspaper stories from 17 US newspapers. The newspaper stories are from two periods that contained major news events, namely the 90 day period around the 9/11 terrorist attacks on New York and the Pentagon and the 90 day period around the Lehman bankruptcy that marked the start of the more severe phase of the financial crisis. We use the LDA model to document three stylized facts of news coverage. First, different newspapers specialize in different topics. For example, we find that the Wall Street Journal allocated more than twice as much coverage to the financial crisis than the average newspaper. Second, the extent of total news coverage allocated to different topics varies over time and depends on what has happened. The September 11 terrorist attacks, the 2008 political party conventions, the Lehman bankruptcy and the failed bailout package proposed by then Secretary of the Treasury Hank Paulson received a large fraction of the overall news coverage following these events. Third, major events make news coverage more homogenous across different outlets. In the days following the events listed above, a majority of the newspapers in our sample devoted more coverage to these events than to any other. Together, these facts suggest that information about major events may be closer to common knowledge than information about minor events.

In order to analyze how the editorial behaviour of news media affects agents' beliefs and decisions, we propose a theoretical model with incomplete information that can replicate the stylized facts documented above. While our empirical analysis is based exclusively on the texts of newspaper articles, the mechanisms that we highlight in the theoretical model apply to all information providers that systematically choose what to report from a large set of events. Our analysis thus encompasses print media, television news and those online information providers that perform an editorial service and present a curated selection of events or news stories.

The model is a two-agent beauty contest game in which each agent's pay-off depends on two factors: The distance of his action to an agent-specific latent variable and the distance between his action and that of the other agent. We take this heterogeneity in agents' pay-off functions as given, but it could arise, for example, because of differences in geographical location or sector membership.

One basic premise of our model is that the dimensionality of the state of the world is too high for individual agents to monitor it on their own. Therefore, they rely on information providers to do so on their behalf. Furthermore, because agents are heterogeneous in terms of what information they find most useful, information providers specialize and cater to their different interests. However, because of a strategic motive, the agents in our model also have an indirect interest in events that are only important for predicting the actions of others. As a result, in some states of the world, all information providers report the same events.

Agents in our model delegate the decision of what to get information about to specialized information providers. These information providers can monitor a larger set of events than they eventually end up reporting. Because their reporting decisions depends on the relative newsworthiness of the realized events, what agents get information about depends on *what has happened*. The model presented here formalizes this editorial function of news media and thus provides a theory of how and why news media focus changes over time. While the model is abstract, it offers several insights that we argue are general.

One such insight is that a reported news story can be informative about more than the event it actually covers, and we derive formal conditions for when a news report about a specific event also reveals information about events that are *not* reported. As an example, consider a person who opens a San Francisco newspaper and finds that it only contains stories about New York. If this person knows that the paper always covers all important San Francisco events, the lack of stories on such events reveals to him that none have actually taken place. Therefore, even though he only reads about New York, he can also update his beliefs about San Francisco. Moreover, because this type of information transmission is a direct consequence of the systematic selection of news stories, agents learn something about the unreported event even if the realizations of the reported and unreported events are independent from one another.

The systematic selection of what gets reported also affects the degree to which knowledge about an event is common among agents. In the related existing literature, signals are generally assumed to be either private or common knowledge, e.g. Morris and Shin (2002), Angeletos and Pavan (2007), Angeletos, Hellwig and Pavan (2007), Hellwig and Veldkamp (2009), Amador and Weill (2010, 2012), Cespa and Vives (2012) and Edmond (2013). In our model, information about a particular event is typically neither private nor common knowledge. Instead, the degree to which knowledge about an event is common among agents is endogenous and depends probabilistically on their preferences and the distribution of events. Because news selection is state-dependent, what agents get information about also influences how probable they think it is that other agents read about the same event.

To see how preferences and the distribution of events together determine the degree to which knowledge about an event is common among agents, consider again a person living in San Francisco. If the San Francisco newspaper reports about some event in Manhattan that normally would be of more interest to a reader from New York, the reader in San Francisco can infer that New Yorkers are probably also reading about that event. However, even though both San Franciscans and New Yorkers are reading about the same event, this event may not be common knowledge: While the San Franciscan can be sure that the New Yorker is also reading about the event on Manhattan, the New Yorker cannot draw a corresponding conclusion since he knows that he has a stronger preference for knowing about events on Manhattan than the person living in San Francisco.

When extreme events such as large terrorist attacks or major financial crises occur, they tend to be reported on the front pages of almost all major newspapers. In the model, individual agents care about the strong actions that other agents will take in response to extreme events even if they do not have a direct interest in the events themselves. Extreme events thus tend to be reported by all information providers. Information about unlikely but extreme events also tends to be closer to common knowledge. To see the role played by the distributions of events for this result, consider a person in New York that reads about a major financial crisis on Wall Street. The San Francisco newspaper will also report about the financial crisis on Wall Street unless an almost equally extreme event has occurred also in San Francisco. If such extreme events are very unlikely, the New Yorker can then infer that a person living in San Francisco is almost surely also a reading about the financial crisis.

The fact that the agents in our model cannot directly observe the entire state of world makes them similar to the rationally inattentive agents in Sims (2003), Mackowiak and Wiederholt (2009, 2010), Alvarez, Lippi and Paciello (2011), Matejka (forthcoming), Matejka and McKay (2015) and Stevens (2014) as well as to agents that need to pay a cost to observe a signal about a pay-off relevant latent variable such as those in Grossman and Stiglitz (1980), Veldkamp (2006a, 2006b), Van Nieuwerburgh and Veldkamp (2009, 2010). The distinctive feature of our set up, from which all of our results follow, is that the agents in our model delegate the decision of what to get information about to specialized information providers that monitor a larger set of realized events before deciding which subset of these events to report. That is, while the agents in the existing endogenous information literature make *ex ante* information acquisition decisions based on the expected usefulness of a particular signal, information providers here decide what to report *ex post*, i.e. after the state of the world has realized. Our setup formalizes the editorial function of news media and captures the fact that the decision to acquire information in many instances is a decision about which information provider to use, rather than a decision about what variable or event to get information about.[1]

Of the existing literature, the papers by Veldkamp (2006b) and Hellwig and Veldkamp (2009) study questions most closely related to those addressed here. Veldkamp (2006b) presents a model in which ex ante identical agents choose asset portfolios and signals simultaneously. If different agents hold different portfolios, they prefer to observe signals about the pay-offs of different assets. However, due to increasing returns to scale in information production, agents tend to purchase similar signals and hold similar portfolios in equilibrium, which can generate *media frenzies* characterized by simultaneous increases in the price and media coverage of a stock. In contrast, our paper studies how widely reported information about an event becomes among agents that have intrinsically different interests.

Hellwig and Veldkamp (2009) analyze a set-up in which agents can choose whether to acquire private or public signals about a single latent variable of common interest. In their set up, public and private signals are equally useful for predicting the latent fundamental. The choice between the two types of signals is then a choice between prediction errors that are correlated with those of other agents and predictions errors that are not. In such a setting, information acquisition inherits the strategic properties of the coordination game and agents want to observe the signals that other agents observe only if their actions are strategic complements. In our model, the information choice determines what agents get information *about* and in some states of the world, agents prefer to know what others know regardless of whether their actions are complements or substitutes.

[1]The motive of our agents is well-captured by Marschak (1960) who writes that *"The man who buys a newspaper does not know beforehand what will be in the news. He acquires access to potential messages belonging to a set called news."*

Gentzkow and Shapiro (2006, 2008), like our paper, study the editorial function of news media, but primarily focus on identifying and analyzing the causes and consequences of ideologically slanted reporting. The political science literature has also studied the role of news journalists and newspaper editors as "gatekeepers" that decide what information gets reported, e.g. Soroka (2006, 2012) and Soroka, Stecula, Wlezien (2014). This literature, too, focuses primarily on documenting and analyzing ideologically or politically biased reporting. While we abstract from such biases, the mechanisms we illustrate apply also to environments in which they are present.

In the next section we document several stylized facts about news coverage using a statistical topic model applied to US newspaper data. Section 3 presents a theoretical model that can replicate the documented facts and we derive formal results based on discrete distributions of events in Section 4. Section 5 we extend the analysis to continuous distributions and Section 6 concludes.

2. Three Stylized Facts of News Coverage

In this section, we estimate a Latent Dirichlet Allocation (LDA) topic model based on texts from a large number of archived newspaper articles. We document three stylized facts about news coverage. In particular, we show that different newspapers specialize in different topics, that the total news coverage devoted to different topics depends on what has happened, and that major events make news coverage more homogeneous across papers.

2.1. **The News Data.** Our empirical analysis focuses on two 3-month periods that contained several major news events. The first period covers the months August to October of 2001 and includes the terrorist attacks on the World Trade center and the Pentagon on September 11. The second period runs from August to October of 2008 and includes the Lehman Brothers bankruptcy that triggered the most severe phase of the financial crisis.

The data we use are parts of news articles obtained from the Dow Jones Factiva database. Factiva contains historical content from more than 30,000 news papers, wire services and online sources from around the world beginning in 1970. We exclude content from wire services since their main audiences are other news organizations. We also limit our data set to articles that appeared either on front pages of US newspapers or on the first pages of their general interest sections.

In total, we obtain data from 14,817 front page articles reported by 17 different US newspapers. The selection of newspapers includes all US newspapers for which we are able to reliably identify the stories that appeared on their front pages or the first pages of their general interest sections. From each of these articles we use a text snippet that typically comprises its first one or two sentences. Table 1 contains an overview of the newspapers in our database as well as corresponding short names that we use in the analysis below. To illustrate the type of information that the text snippets contain, Table 2 shows a number of examples.

2.2. **Latent Dirichlet Allocation.** To extract topics from our text corpus, we estimate a Latent Dirichlet Allocation (LDA) topic model. Introduced in Blei et al (2003), the LDA

Table 1. Newspapers in Database

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		

Notes: The table shows the full names of the newspapers whose front-page articles are in our text corpus. It also shows corresponding short names used in the empirical analysis below. Newspapers that have changed their names over time or have merged are combined into one entry.

model is one of the most-widely applied tools in machine learning and natural language processing. A topic is defined by a frequency distribution of words and the topics are estimated from the text corpus. Variants of the LDA model have been used, for example, to identify scientific topics (Griffiths and Steyvers, 2004) and to classify micro blogs (Ramage et al, 2010). The first application to economics or finance that we are aware of is Mahajan, Dey and Haque (2008), who used it to classify financial news articles. More recently it has also been used by Bao and Datta (2014) to discover risk-factors disclosed in annual corporate filings. Furthermore, Fligstein, Brundage and Schultz (2014) as well as Hansen, McMahon and Prat (2015) have used LDA models to analyze FOMC transcripts.

Using an LDA model allows us to discover and quantify the topics of a very large number of news texts without relying on manual classifications or pre-defined categories. Moreover, because LDA defines articles as mixtures of different topics, it can accommodate the fact that many news stories talk about more than one specific issue. For example, it can capture that an article about a government bailout package may discuss both politics and financial markets.

The main parameter of choice researchers need to set before estimating an LDA model is the number of topics. Once this number has been set, the actual topics are formed endogenously and are thus outputs of the estimated model. Relative to approaches that use word counts to measure news coverage, e.g. Baker, Bloom and Davis (2013), the LDA does therefore not require researchers to pre-specify words or topics of interest. Another desirable property of LDA is that it captures not only changes in the importance of a topic over time, but also how important that topic is in an absolute sense.

The text data or corpus used for estimating an LDA topic model is described by a *vocabulary*, which is a list of all words that it contains, and *documents*, which are partitions of the text corpus. In our case, each text snippet from a news article is one document, and all text snippets together form the corpus. Generally speaking, an LDA topic model can be

Table 2. Sample Text Snippets of Newspaper Articles in the Database

Text Snippet	Newspaper	Publication Date
"An 18-year-old student who wounded five people at his suburban San Diego high school earlier this year committed suicide, hanging himself with a sheet in his jail cell. The student, Jason Anthony Hoffman, pleaded guilty last month in the ..."	The New York Times	2001/10/31
"Passengers returned to US airports in increasing numbers yesterday to find long lines, layers of new security and limited service. But many travelers were able to reach their destinations as more than a third of the usual number of ..."	The Washington Post	2001/09/15
"A day after dividing their votes on a failed proposal for a 700 billion Wall Street bailout, Maines two US House members agreed Tuesday that its vital for lawmakers to pass a relief bill for credit markets."	Portland Press Herald	2008/10/01
"In a case that could have dramatic consequences for school districts and towns across Pennsylvania, the state Supreme Court will hear arguments today on the constitutionality of the commonwealths property-tax system, which raises more ... "	The Philadelphia Inquirer	2008/09/10

Notes: The table shows examples of the text snippets used to estimate the LDA topic model below. The text snippets were extracted from the Dow-Jones Factiva database. The dates shown are those on which the articles were originally published in the print-editions of the respective newspapers.

thought of as a latent structure that could have generated the observed text corpus following probabilistic rules. It is parameterized by (i) a distribution over topics that determine the probability that a document belongs to a topic and (ii) a distribution over the words in the vocabulary that defines each of the topics. In the LDA framework, each document in a corpus can be thought of as having been generated by the following steps:

(1) Draw a set of topic weights from the corpus-specific distribution over topics.
(2) Draw N topics from this document-specific topic distribution, with N being the number of words in the document

(3) Draw one word from each of these N topics.

To describe the LDA model more formally, we index topics by $k \in \{1, 2, ..., K\}$, documents by $d \in \{1, 2, ..., D\}$, words in the vocabulary by $v \in \{1, 2, ..., V\}$, and words in a document by $n \in \{1, 2, ..., N\}$. The probability of a specific text corpora being generated is then given by the probability density function

$$p(\beta, \theta, z, w) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n} \mid \theta_d) \, p(w_{d,n} \mid \beta_{1:K}, z_{d,n}) \right) \tag{2.1}$$

where β, θ and z are unobserved parameters. The rows of the $K \times V$ matrix β contains the word distribution β_k for topic k, the columns of the $K \times D$ matrix θ contains the topic proportions θ_d of document d so that $\theta_{k,d}$ is the proportion of words in document d drawn from topic k. The topics assignment of document d is z_d so that word n in topic d is drawn from topic $z_{d,n}$. The density (2.1) depends on the text corpus through the matrix w, defined so that the words observed in document d is the vector w_d and $w_{d,n}$ is word n in document d.

There are two underlying properties that are important for understanding how the LDA is used to extract topics from the text corpus. First, LDA is a mixed membership model. This implies that each document may belong to different topics to different degrees. As discussed above, this is helpful for our application as it allows newspaper articles to be treated as belonging to several topics at the same time. For example, an article could be classified as belonging to the topics *financial crisis* and *congressional politics* with topics weight 0.4 and 0.6, respectively. Second, the order and grammatical structure of words within documents is assumed to be irrelevant. This so-called "bag-of-words" assumption simplifies the latent probabilistic structure of the text corpus while retaining the information relevant for discovering the topics that the corpus contains.

In order to apply Latent Dirichlet Allocation to an observed text corpus, the generative process described above needs to be inverted. The posterior distribution for the latent parameters conditional on the text corpus can be formed by dividing the density (2.1) by the probability of observing that corpus

$$p(\beta, \theta, z \mid w) = \frac{p(\beta, \theta, z, w)}{p(w)}. \tag{2.2}$$

Evaluating the denominator in (2.2) is computationally infeasible as it entails integrating over the distributions of the latent parameters. However, there are several methods that can be used to approximate the posterior distribution, see Asuncion, Welling, Smyth and Teh (2009). Here, we rely on the collapsed Gibbs sampling algorithm of Griffiths and Steyvers (2004) to estimate β, θ and z . Both the limited number of discretionary decisions required for the LDA estimation and the fact that topics emerge from the analysis without having to pre-define them are particularly attractive for our application. These properties allow us to analyze the documents in our database in an objective and replicable manner.

2.3. **Estimation.** To be able to estimate the LDA model using the approach described above, we first have to translate the raw newspaper texts into a vector-space representation that captures their word frequencies. For this, we break the text down into single words and remove a number of very common terms that have little informative value in bag-of-words models, see Blei et al (2009). Then, we remove word-suffixes using the Porter (1980) stemming algorithm. This step allows us to group closely related words such as "presidential" and "president" or "worker" and "workers"and thus reduces the size of the resulting vector space. For computational reasons, we also limit our vector-space to words that occur at least 100 times.

The number of topics in the benchmark model is set to 10. While choosing a larger number can generally result in more of the topics having a clear interpretation, it can also yield a classification that is too fine for subsequent analyses.[2] We estimate a single LDA model using the texts from both 2001 and 2008 jointly. This allows for the possibility that some topics are recurrent and reported with a terminology that is stable over time. For instance, the vocabulary used in sports related articles may change little over time and form a topic that is present in news articles in both 2001 and 2008.[3]

Table 3. Estimated LDA Topics: High-Probability Words

Topic	Words with the highest assigned probabilities (in descending order)
1	bush presid washington afghanistan unit state militari taliban war attack
2	democrat john republican obama mccain presidenti campaign barack sen senat
3	school year student counti high state univers review journal colleg
4	year old home ago time day just peopl like famili
5	financi washington billion market hous bush bank feder crisi govern
6	state million year plan new citi health compani say propos
7	mail daili staff charleston west counti said virginia st state
8	yesterday polic said offic anthrax court feder offici investig charg
9	attack new terrorist york world center sept trade airport airlin
10	citi new today palestinian aug georgia west day isra south

Notes: For each of the 10 topics estimated using Latent Dirichlet Allocation, the table shows the 10 words with the highest probabilities of occurring in that topic. The order of words is descending in terms of the probabilities assigned to them in the given topic. All words have been stemmed using the Porter (1980) stemmer.

2.4. **Estimated LDA Topics.** The LDA model estimated topics endogenously, but human input is generally required to interpret the resulting topics, and in our case, associate them with particular events. Table 3 shows the topics identified by our estimated LDA model in terms of their highest-probability words. We find that several of the topics that emerge from our estimation are intuitively meaningful. For example, Topic 1 relates to the war in Afghanistan, Topic 2 relates to the candidates of the 2008 US presidential elections, and Topic

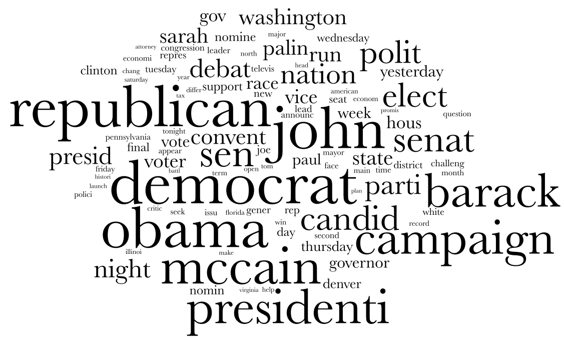
[2]In the Online Appendix, we also present results from the LDA model using 5, 20, 50 and 100 topics.

[3]If no topic occurs in both periods and when the number of documents are approximately the same for the two periods, estimating a joint LDA model for both time periods with 10 topics should yield the same topics and assigned topics weights as if we were to estimate two separate models with 5 topics for each period.

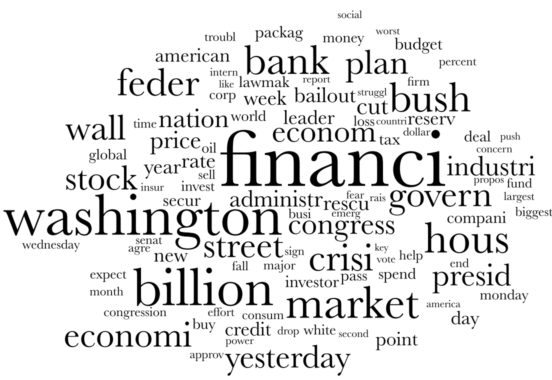
Figure 1. Estimated LDA Topics: Word Clouds of Selected Topics

Topic 1: Afghanistan

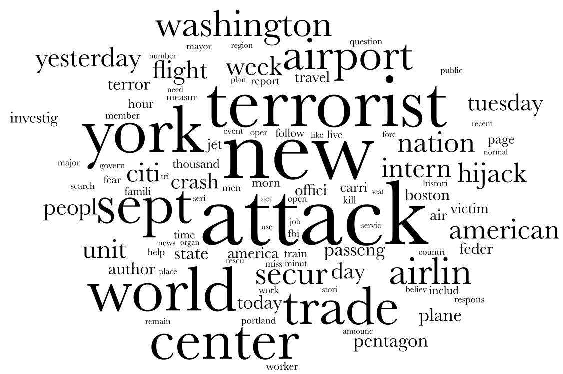
Topic 2: 2008 Presidential Candidates



Topic 5: Financial Crisis and Bailouts



Topic 9: Terror Attacks



Notes: The word-clouds illustrate the probabilities associated with specific words in the topics estimated using Latent Dirichlet Allocation. Words with higher probabilities are shown in a larger size. All words were stemmed using the Porter (1980) stemmer. The topics correspond to those shown in table 3.

9 covers the September 11 terrorist attacks. Furthermore, a relatively clear interpretation can also be attached to Topic 5, which seems to capture both the financial crisis and the reactions of the US government to it.[4]

Some topics identified by the LDA model are not associated with easily identifiable real world events, e.g. Topic 4. The presence of such difficult-to-interpret topics is a common feature of LDA models, see Chang, Gerrish, Wang, Boyd-Graber and Blei (2009) and is

[4]In the Online Appendix, we report the first sentence of each article that were assigned the highest probability of belonging to each of the topics.

the result of less frequent "true" topics being combined into one residual model topic. Accordingly, the fraction of difficult-to-interpret topics typically decreases when the number of topics is increased.[5]

Topics 1,2,5, and 9 all appear to be associated with separate and well-defined events. To get a more complete understanding of these four topics and their associated word probabilities, we also illustrate them in the form of word clouds (Figure 1). These graphical representations show a larger number of words for each topic, reflecting their probabilities within a given topic in terms of the sizes at which they are displayed.[6] The interpretations of the four topics that we derive based on the word clouds reinforces the ones obtained from the high-probability words shown in Table 3.

2.5. **Different Newspapers Specialize in Different Topics.**

The first specific aspect of newspaper coverage that we assess using the estimated LDA model concerns the extent to which newspapers are specialized. In other words, we investigate if and by how much different newspapers tend to over- or underweight different topics relative to the overall average. For this purpose, Figure 2 plots normalized deviations of newspaper-specific topic probabilities for the same four topics discussed above. We calculate these normalized deviations as

$$d_{i,j} = \frac{p_{i,j} - p_j}{p_j} \tag{2.3}$$

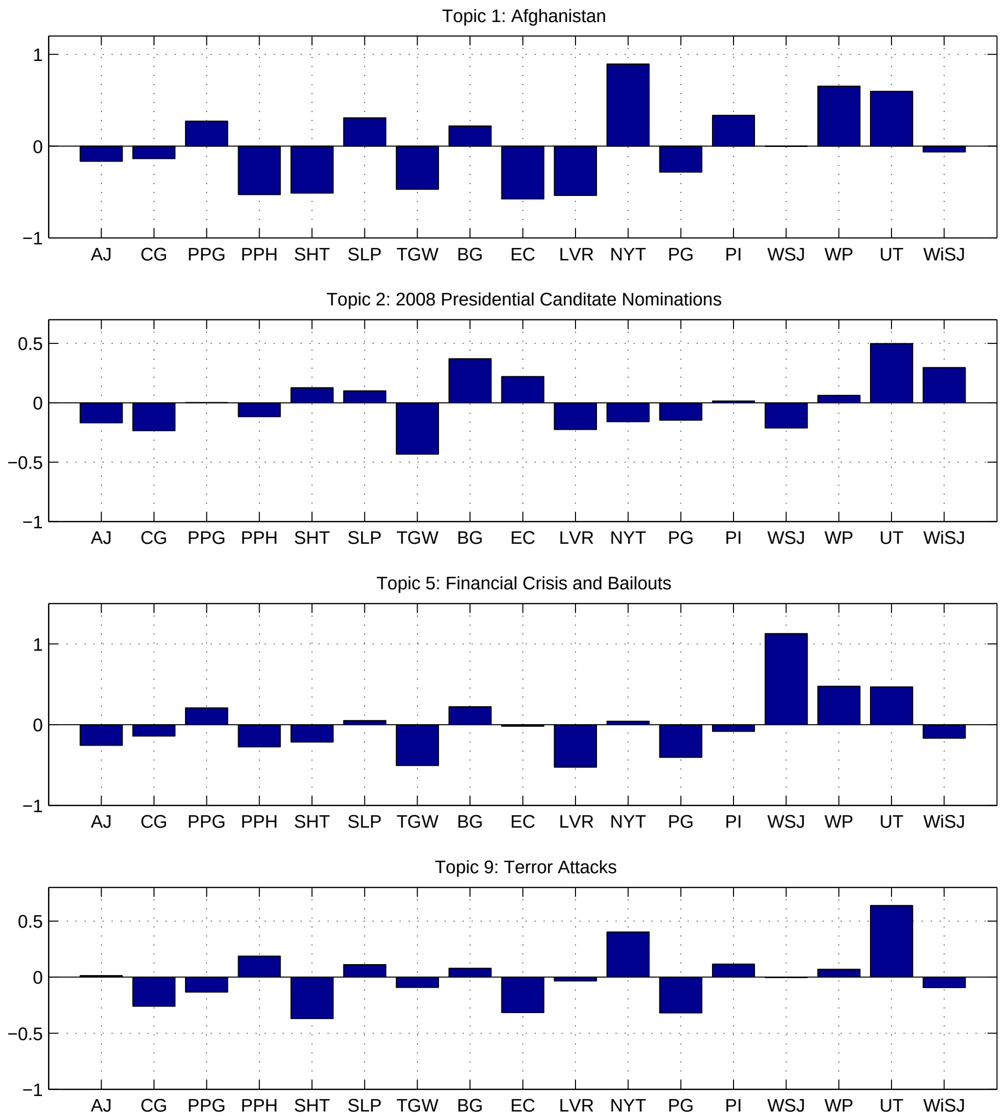
where $p_{i,j}$ denotes the probability that newspaper i reports on topic j and $p_j = \frac{1}{I}\sum_{i=1}^{I} p_{i,j}$ being the corresponding average across all I newspapers. A positive unit deviation thus implies that a newspaper devoted 100 per cent more coverage to a topic relative to the average newspaper, a negative deviation implies that the newspaper devoted less coverage to a topic than the average news paper. (A negative unit deviation would imply zero coverage of a topic.)

The plots document that there are large amounts of variation in terms of which newspapers tend to cover which topics. For example, the financial crisis as captured by Topic 5 received more than twice as much coverage in the Wall Street Journal than it did in the hypothetical average outlet. Similarly, both the New York Times and USA Today allocated a larger fraction of their news coverage to the September 11 terror attacks than the average newspaper in our sample. These deviations suggest that newspapers do indeed specialize, resulting in coverage that is heterogeneous in the cross-section of outlets and that the measured specialization conforms to our priors about the target audiences of the most widely read national newspapers.

[5]In the Online Appendix, we list the 10 most frequent words for each topic for the LDA model estimated with the number of topics set to 100. There, one can see that for instance the 9/11 terrorist attack topic is split into several sub-topics, with one topic covering the actual attacks, another topic more closely related to who the suspected perpetrators were, another topic related to the US military response to the attacks, and so on.

[6]Word clouds are not to everyone's liking, see $http://www.wordle.net/show/wrdl/718619/I\_hate\_word\_clouds$.

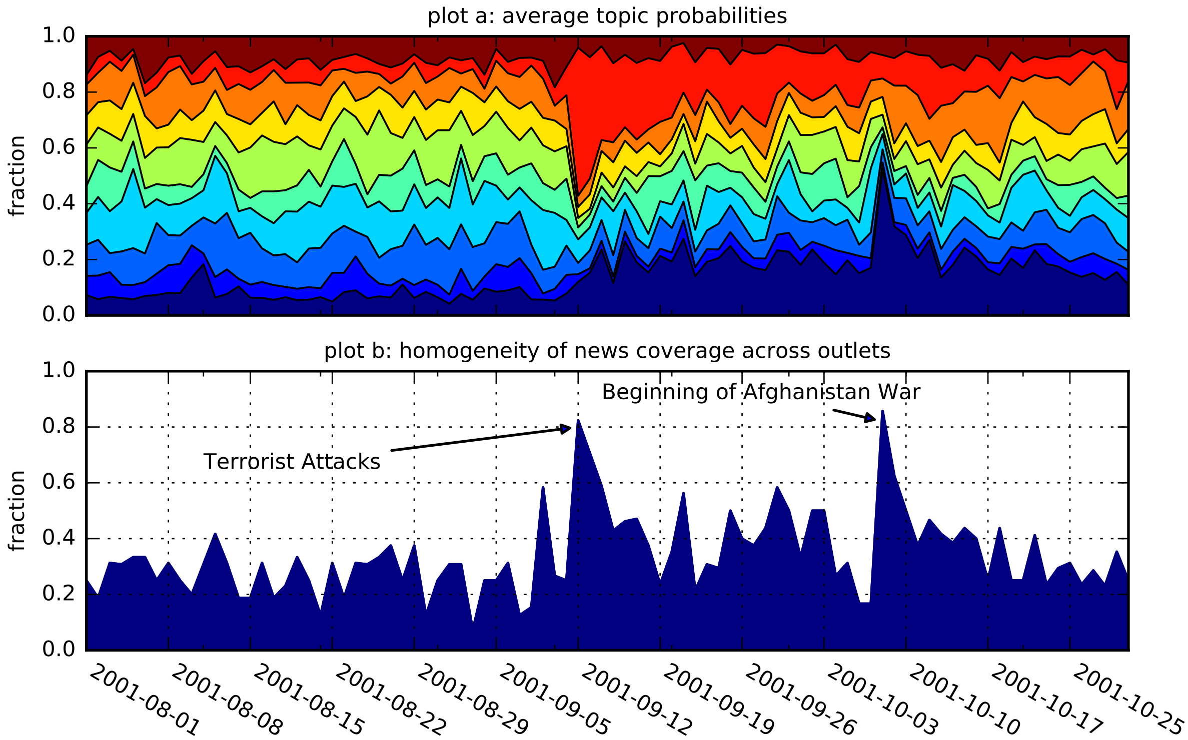
FIGURE 2. Newspaper Specialization: Probabilities of Selected Topics



Notes: The figure illustrates the specialization of newspapers on different topics. The topics correspond to those shown in figure 1 and table 3. The short names of newspapers correspond to those in table 1. The normalized topic-specific deviations of news focus are calculated as $d_{i,j} = \frac{p_{i,j}-p_j}{p_j}$, with $p_{i,j}$ denoting the probability that newspaper i reports on topic j and $p_j = \frac{1}{I}\sum_{i=1}^{I} p_{i,j}$ being the corresponding average across all I newspapers. A positive unit deviation implies that a newspaper devoted 100 per cent more coverage to a topic relative to the average newspaper, a negative deviation implies that the newspaper devoted less than average coverage to a topic.

2.6. **Major Events Shift News Focus and Increase the Homogeneity of News.** We can now assess how major events affect news coverage along two specific dimensions: the average emphasis specific topics receive, as well as the homogeneity of news coverage

FIGURE 3. 2001 Terror Attacks: Time-Variation of Average Topic Probabilities and Homogeneity of Coverage Across Newspapers

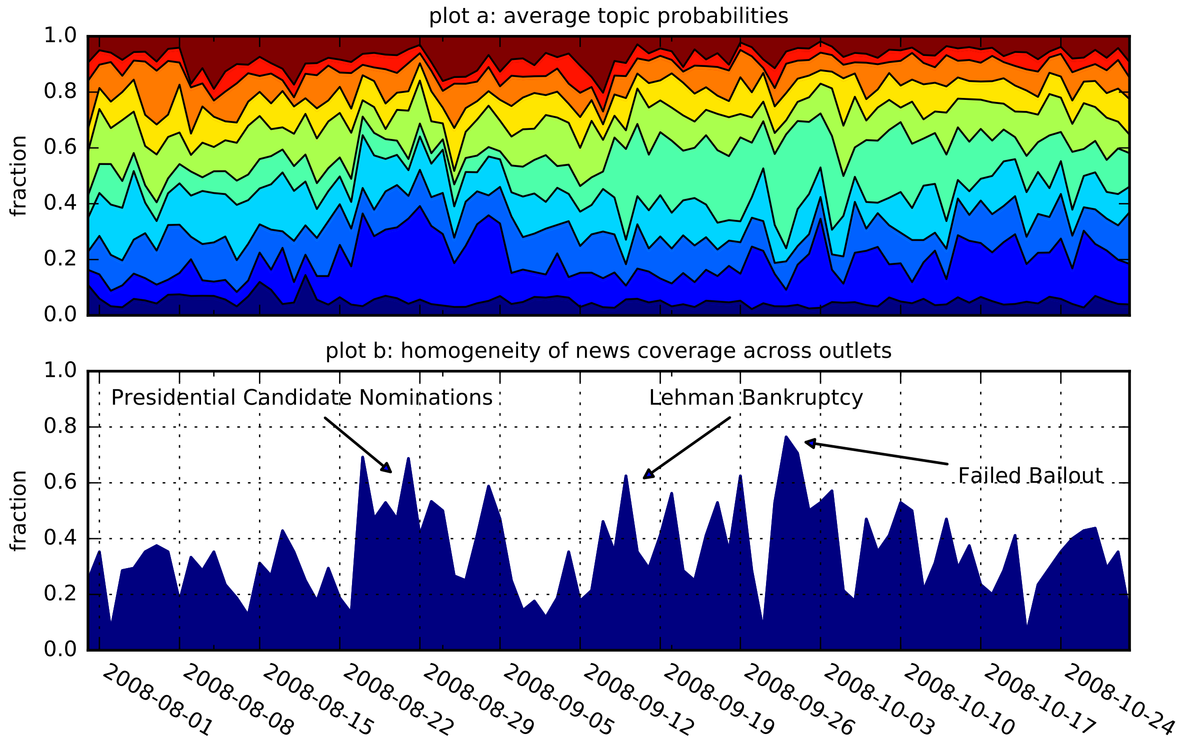


Notes: The figure illustrates time-series variation in the probabilities assigned to the estimated topics and the cross-sectional homogeneity in newspaper coverage. Each topic is represented by a separate color. The time-horizon shown is 08/01/2001 to 10/31/2001. Only days with coverage of at least 10 newspapers are shown. The topics correspond to those shown in Table 3 with Topic 1 at the bottom and Topic 10 at the top. The topic probabilities for a specific day shown in plot a are defined as the simple average of the corresponding probabilities of all articles in the database for that day. The homogeneity measure shown in plot b is defined as the fraction of newspapers for which the highest-probability topic is the same one that also carries the highest probability across all articles published on that day.

in the cross-section of outlets. To do so, we explore time variation in the estimated topic probabilities as well as their distribution across newspapers. If major events do indeed affect the focus of news coverage and its cross-sectional homogeneity, we would expect the September 11 terrorist attacks, the nominations of presidential candidates and the outbreak of the financial crisis to be associated with such a behavior.

To assess if this is the case, we use two different measures. First, we calculate overall topic probabilities at a daily frequency by averaging the estimated topic probabilities of all stories in our database for a given day. The fraction $F_{t,k}$ of total news devoted to topic k at date t

FIGURE 4. 2008 Financial Crisis: Time-Variation of Average Topic Probabilities and Homogeneity of Coverage Across Newspapers



Notes: The figure illustrates time-series variation in the probabilities assigned to the estimated topics and the cross-sectional homogeneity in newspaper coverage. Each topic is represented by a separate color. The time-horizon shown is 08/01/2008 to 10/31/2008. Only days with coverage of at least 10 newspapers are shown. The topics correspond to those shown in Table 3 with Topic 1 at the bottom and Topic 10 at the top. The topic probabilities for a specific day shown in plot a are defined as the simple average of the corresponding probabilities of all articles in the database for that day. The homogeneity measure shown in plot b is defined as the fraction of newspapers for which their highest-probability topic is the same one that also carries the highest probability across all articles published on that day.

is thus given by

$$F_{t,k} \equiv \frac{\sum_d \theta_{t,d,k}}{D_t} \tag{2.4}$$

where $\theta_{t,d,k}$ is the probability that article d from date t belongs to topic k and D_t is the total number of articles in the sample from day t.

Second, to assess homogeneity in news-coverage across newspapers, we consider to what extent the outlets agree on which topic is most important on a given day. For this, we first identify the topic that has the highest probability across all articles of a given day. Then, we calculate the fraction of newspapers that assign the highest weight to that same topic, i.e. homogeneity H_t of news coverage on day t is defined as

$$H_t \equiv \frac{\sum_m \mathcal{I}\left(\arg\max_k F_{t,m,k} = \arg\max_k F_{t,k}\right)}{M} \tag{2.5}$$

where $\mathcal{I}$ is an indicator function that takes the value 1 when the equality in brackets holds. $F_{t,m,k}$ is the fraction of news coverage devoted to topic k by newspaper m at time t and M is the total number of newspapers. The range of H_t is thus between 0 and 1, with 1 indicating that all newspapers agree on which topic is the most important one.

Figure 3 shows the evolution of both of these measures for the period August to October 2001. The top panel illustrates the share each topic received on each date in the first sample. Topics are ordered from below, with Topic 1 at the bottom and Topic 10 at the top. The most striking episode occurs on September 12 and the following days when more than half of the total news coverage was devoted to the terrorism topic (Topic 9) as displayed in light red. A second pronounced change occurs on October 8, the day after the war in Afghanistan began (Topic 1) as displayed in dark blue. As can see from the bottom panel, the same two days are also associated with sharp increases in topic homogeneity. That is, both the terror attacks and the beginning of the Afghanistan war caused coverage to become more similar across newspapers.

For the second period used in our analysis, i.e. August to October 2008, the same exercise is repeated in Figure 4. Here, too, several events stand out in the sense that they seem to affect both the focus of news coverage and its cross-sectional homogeneity. First, Topic 2, which relates to the presidential nomination conventions, received high levels of media coverage in late August and early September and caused an increase in homogeneity. Then, the Lehman Brothers Bankruptcy on September 15 caused another spike. Finally, a last big spike in the homogeneity measure occurs on September 30, the day after the Emergency Economic Stabilization Act of 2008 failed to pass the US House of Representatives.

The 9/11 terrorist attacks, the war in Afghanistan, the presidential candidate nomination conventions, the Lehman bankruptcy and the failed financial bailout package are all events that robustly and substantially increase the relative level of homogeneity of news coverage across specifications with different number of topics. In the Online Appendix, we plot the graphs for how the homogeneity of news coverage evolve over time when we allow for 5, 10, 20, 50 or 100 topics. Increasing the number of topics affect the topic assignment and our heterogeneity measure in two distinct ways. First, with more topics, individual topics are better defined and may be assigned a higher weight as they may better describe the actual topics of news articles. Second, with many topics, a given event may also give rise to several sub-topics. This effect may decrease our measure of news homogeneity. However, a larger number of topics reduces the average level of homogeneity: The sample average of our measure homogeneity measure H_t decreases from about 50 per cent with 5 topics to about 20 per cent in the specification with 100 topics. So while the peaks of the homogeneity measure are somewhat lower with 50 or 100 topics, the relative change in homogeneity after a major news event may still increase when we allow for a larger number of topics.

3. A Beauty Contest Model with Delegated Information Choice

Above we documented three stylized facts about news coverage that can be attributed to the editorial decisions of newspapers. We saw that newspapers specialize their coverage and on average provide different degrees of coverage of different topics. However, when major events occur, their coverage becomes more similar. The data was restricted to US newspapers, but it is likely that the editorial decisions of other information providers, such as cable tv news or online news sites, display a similar pattern.

In what follows, we present a theoretical model that can reproduce the documented facts and also help us understand how the editorial decisions of information providers affect agents' beliefs and actions. The model is an abstract beauty contest game in the spirit of Morris and Shin (2002) in which agents' pay-offs depend on the distance of their actions from a latent variable as well as the distance of their action from other agents' actions. However, we depart from the original model in two important ways.

First, agents have heterogenous interests in the sense that different agents want their actions to be close to different latent variables. Second, agents are constrained in the number of stories that they can read about and therefore delegate the information choice to specialist information providers that can monitor a large set of events on the agents' behalf. Each information provider is characterized by a *news selection function*, which is a mapping from states of the world to a set of reported events. The news selection functions formalize the editorial decisions of news media and below we will analyze how they affect agents' beliefs and ability to coordinate their actions. For concreteness, we will refer to the information providers in the model as "newspapers" and say that information consumers "read" about a story, though the analysis applies equally well to TV and radio broadcasters and online news media.

3.1. **Information consumers with heterogeneous interests.**

Our model is populated by two information consumers, Alice and Bob. They live in a world with two *potential stories,* X_a and X_b. A potential story $X_i : i \in \{a, b\}$ is a random variable that takes values in $\mathcal{X}$ and an *event* x_i is a particular realization of X_i. The state of the world is described by the pair $(x_a, x_b) \in \Omega$ where $\Omega = \mathcal{X} \times \mathcal{X}$ is the set of all (joint) events. We say that an event is of interest to Alice or Bob if their utility increases as a result of knowing about it.[7]

3.1.1. *Utility and heterogenous interests.*

Alice and Bob have different interests and this heterogeneity is introduced via their utility functions. The basic set-up is a two person beauty contest game in which Alice's utility depends on the distance between her action y_a and the latent variable x_a as well as the distance between her action and Bob's action y_b. This is formalized by the following utility function for Alice

$$U_a = -(1-\lambda)(y_a - x_a)^2 - \lambda (y_a - y_b)^2 . \tag{3.1}$$

where $\lambda \in (-1, 1)$ is a parameter that governs Alice's strategic motive. If Bob also wanted to take an action that was close to x_a and close to Alice's action y_a this setup would be a

[7] Here we use the word *event* to mean a specific story that a newspaper might report about, i.e. a realized outcome of X_i . This use is more restrictive than how the word is used in the probability theory where "event" describes any set of outcomes that can be assigned a probability.

two-person version of the beauty contest in Morris and Shin (2002). However, we introduce heterogeneity by making Bob want to take an action that is close to x_b rather than x_a. Bob's utility function U_b is otherwise symmetric to Alice's and given by

$$U_b = -(1-\lambda)(y_b - x_b)^2 - \lambda (y_b - y_a)^2 \tag{3.2}$$

where y_a is the action taken by Alice. We say that Alice has a direct interest in X_a because her utility depends directly on the realized value of X_a. Symmetrically, Bob has a direct interest in X_b. The parameter λ governs the strength of the strategic motive. Because of this strategic motive, Alice has an indirect interest in knowing about X_b since that may help her better predict Bob's action. Symmetrically, Bob has an indirect interest in knowing about X_a.

Alice's optimal action y_a is given by the first order condition

$$y_a = (1-\lambda) E_a[x_a] + \lambda E_a[y_b] \tag{3.3}$$

where E_a denotes the expectations operator conditional on Alice's information set. (A symmetric expression describes Bob's optimal action.) If agents could observe both x_a and x_b directly, the equilibrium action would be described by

$$y_i = \frac{1}{1+\lambda} x_i + \frac{\lambda}{1+\lambda} x_j : i, j \in \{a, b\}, i \neq j \tag{3.4}$$

However, Alice and Bob observe neither x_a nor x_b directly and instead have to rely on information providers who monitor the state of the world on their behalf.

3.2. **Information providers.** There are two information providers, which we call Paper A and Paper B. News stories are to some extent indivisible in the sense that reading one word about many different stories is less useful than reading a full paragraph about fewer stories. News media with finite space thus need to select what to report. It is also not feasible for an individual to read all stories that are reported in every newspaper. To capture this constraint, Alice and Bob are restricted to reading only one paper each.[8] Alice reads Paper A because it reports those stories that she finds most interesting. Similarly, Bob reads Paper B because it reports those stories that he finds most interesting. While not modeled explicitly here, this is a simple way of capturing that newspapers compete for readers/subscribers by offering specialized content.

We formalize the editorial decision of a newspaper by defining its news selection function as a mapping from the realized state of the world into a discrete decision of what to report.

Definition 1. *The news selection function $\mathcal{S}_i : \Omega \to \{0, 1\}$ is an indicator function that takes the value* 1 *when paper i reports the realized value of X_i and* 0 *otherwise.*

Depending on the state of the world, Alice observes either X_a or X_b. Both newspapers make their editorial decisions in order to maximize the expected utility of their readers. In

[8] It would be straightforward to endogenize the decision of how many newspapers each agent chooses to read. A fixed cost of reading a newspaper that is large enough to discourage Alice and Bob from reading both newspapers while not being so large as to make it prohibitively expensive to read one newspaper would result in an outcome identical to the set up posited by assumption here.

doing so, they take the news selection function of the other newspaper as given. The news selection functions are thus determined by

$$\mathcal{S}_i\left(x_i, x_j\right) = \arg\max_{\mathcal{S}_i} E\left[U_i\left(\mathcal{S}_i, \mathcal{S}_j\right)\right] \tag{3.5}$$

where the expression makes it clear that the expected utility of an agent depends not only on the news selection of the paper that he or she reads but also on the utility function of, and the news selection function of the paper read by, the other agent.

3.3. **News selection and beliefs.** Reading a news report about either X_a or X_b is always immediately informative about that specific variable. However, one implication of a systematic news selection is that whether an event is reported or not is by itself informative. We state this result more formally in the following proposition.

Proposition 1. *Posterior beliefs about the unreported story x_j coincide with $p\left(x_j \mid x_i\right)$ only if the probability of reporting about x_i is conditionally independent of x_j, that is*

$$p\left(x_j \mid \mathcal{S}_i = 1, x_i\right) = p\left(x_j \mid x_i\right) \tag{3.6}$$

only if

$$p\left(\mathcal{S}_i = 1 \mid x_i\right) = p\left(\mathcal{S}_i = 1 \mid x_j, x_i\right). \tag{3.7}$$

Proof. By Bayes' rule we can express the posterior about the unreported variable as

$$p\left(x_j \mid \mathcal{S}_i = 1, x_i\right) = \frac{p\left(\mathcal{S}_i = 1 \mid x_j, x_i\right)}{p\left(\mathcal{S}_i = 1 \mid x_i\right)} p\left(x_j \mid x_i\right). \tag{3.8}$$

It then follows immediately that (3.6) holds only if

$$\frac{p\left(\mathcal{S}_i = 1 \mid x_j, x_i\right)}{p\left(\mathcal{S}_i = 1 \mid x_i\right)} = 1 \tag{3.9}$$

which completes the proof. □

Proposition 1 is general and holds for all distributions of X_a and X_b, but a special case is particularly illustrative of its implications. Consider a set up where X_a and X_b are independent so that $p\left(x_j \mid x_i\right) = p\left(x_j\right)$. Knowing about x_i is then by itself uninformative about x_j. But Proposition 1 states that if the probability of reporting x_i depends on the realized value of X_j, the fact that x_i was reported *is* informative about x_j. The systematic news selection by the information providers thus makes agents update their beliefs about both reported and unreported events, even when the two events by themselves are uninformative about each other.

The implications of Proposition 1 are starkest if there are states of world where paper i would report X_j instead of X_i. Since paper i did not report X_j, these states can then be ruled out, i.e. these states are associated with a zero probability conditional on $\mathcal{S}_i = 1$ and x_i. As an example, consider somebody reading the Wall Street Journal. If there is no report about a stock market crash, the reader can infer that no stock market crash has occurred since the Wall Street Journal would for sure have reported such an event, had it occurred.

4. News selection, commonality of information and correlated actions

We first study the implications of delegated information choice for agents beliefs and actions in a simple setting where the state space of the random variables X_a and X_b is low-dimensional and discrete. While we relax these assumptions in Section 5, the simple set up here allows us to derive explicit expressions for agents' optimal actions and the degree to which information is common across agents. It also enables us to establish analytically how delegated information choice affects the correlation between agents' actions.

4.1. Discrete states of the world.

Consider a world where the potential stories X_a and X_b are discrete random variables that can take the values $-1, 0$, or 1. The different states occur with probabilities given by

$$p_i(-1) = \frac{1}{4}, p_i(0) = \frac{1}{2}, p_i(1) = \frac{1}{4} : i \in \{a, b\} \tag{4.1}$$

where $p_i(x_i)$ is the pmf of x_i. The potential stories X_a and X_b are thus identically and symmetrically distributed, zero mean random variables. We also assume that X_a and X_b are independent of one another so that

$$p_i(x_i \mid x_j) = p_i(x_i) : i \neq j, \in i, j \{a, b\}. \tag{4.2}$$

Neither the symmetry nor the independence of X_a and X_b are necessary for what follows, but help simplify the presentation.

4.2. Optimal news selection functions.

Each information provider chooses which story to report in order to maximize the expected utility of its respective reader. Because of the strategic motive in agents' utility, what information will be most useful to Alice depends on Bob's action. Since Bob's action in turn depends on what information he has available, the news selection function of Paper A depends on the news selection function of Paper B. A Nash equilibrium in the news selection game is a fixed point at which neither newspaper wants to change its selection function, taking the other paper's selection function as given. To find such an equilibrium, we first conjecture optimal news-selection functions (without proof of optimality) and derive optimal actions that take them as given. It is then straightforward to verify that the news-selection functions we postulate do indeed constitute a Nash equilibrium.

4.2.1. *No strategic motive.*

As a benchmark, consider first the case in which $\lambda = 0$ and where agents' thus do not have an incentive to coordinate. In this case, it is optimal for Paper A to always report X_a since Alice's utility then depends neither directly nor indirectly on X_b. Symmetrically, it is optimal for Paper B to always report X_b. In the absence of a strategic motive in actions, the news selection functions are thus simply described by

$$\mathcal{S}_i = 1 \ \ \forall \ \{x_i, x_j\} \in \Omega. \tag{4.3}$$

The news selection functions for Paper A and Paper B when $\lambda = 0$ are also given in tabular form in the top row of Table 1.

4.2.2. *Strategic complementarity.* When agents have an incentive to take actions that are close to the action of the other agent, i.e. when $\lambda > 0$, the equilibrium news selection function is described by

$$\mathcal{S}_i = \begin{cases} 0 & \text{if } x_i = 0 \text{ and } x_j \in \{-1, 1\} \\ 1 & \text{otherwise} \end{cases} . \tag{4.4}$$

Paper A will then report X_a when X_a equals -1 or 1 but report X_b if $X_a = 0$ and X_b equals -1 or 1. Again, the news selection functions are given in tabular form in Table 1.[9] The central column in the bottom left panel describes what Paper A reports when $x_a = 0$ with a B indicating that Paper A reports X_b. The center row of the bottom right panel describes what Paper B reports when $x_b = 0$ with a symmetric interpretation.

As in the case without strategic motives, Paper A will report about X_a most of the time. However, when Alice wants to take an action that is close to Bob's action, it is optimal for Paper A to report about X_b in states of the world when $x_a = 0$ and $x_b \neq 0$. The intuition is simple. When the realized value of X_a is zero, it is more important for Alice to know whether Bob will take a positive or negative action. Knowing the realized value of X_b is then more useful to Alice since she can then better predict Bob's action.[10]

4.2.3. *Strategic substitutability.* Changing the sign of λ so that agents want to take actions that are far from the actions of the other agent leaves the equilibrium news selection functions unchanged. When $x_a = 0$, it is still more useful to Alice to observe X_b so that she knows whether Bob took a positive or negative action so that she can take an action in the opposite direction. Thus, regardless of whether λ is positive or negative, there are states of the world in which Alice and Bob want to know what the other agent knows.

This contrasts with the result in the coordination game in Hellwig and Veldkamp (2009). There, ex ante identical agents can chose to observe different combinations of private and public signals about a single latent variable of common interest. In such a setting, information acquisition inherits the strategic properties of the coordination game. Thus, if there is a strategic complementarity in actions, agents also want to buy the same signals as other agents. The different implications arise from the fact that in Hellwig and Veldkamp's model, agents do not choose what to get information *about*, but rather if the noise in a signals is common to all agents or idiosyncratic. Clearly, public and private signals of the same precision are equally useful for predicting the latent fundamental. The choice between private and public signals faced by an agent in the model of Hellwig and Veldkamp is thus a choice about having prediction errors that are positively correlated or uncorrelated with the prediction errors of other agents. With strategic complementarities, the former is preferred, with strategic substitutes, the latter. In our model, the information choice determines whether an agent makes an error in predicting the action of the other agent or not. When actions

[9] Sufficiently strong complementarities result in multiple equilibria in news selection strategies. This case is discussed in the Online Appendix.

[10] In fact, given the news selection function (4.4), Alice can infer that if she reads about X_b, then $x_a = 0$ with probability 1. However, that Alice can infer the realized value of the unreported value with certainty is to some degree an artefact of the low dimensional state space. (Proposition 1 above provided a more general characterization of the posterior beliefs about the unreported event, conditional on what was reported.)

are either strategic complements or substitutes, not knowing the action of the other agent is costly.

Table 1: News selection functions

Paper A / **Paper B**

No strategic motive $\lambda = 0$

ω	$x_a = -1$	$x_a = 0$	$x_a = 1$	ω	$x_a = -1$	$x_a = 0$	$x_a = 1$
$x_b = -1$	A	A	A	$x_b = -1$	B	B	B
$x_b = 0$	A	A	A	$x_b = 0$	B	B	B
$x_b = 1$	A	A	A	$x_b = 1$	B	B	B

Strategic motive $\lambda \neq 0$

ω	$x_a = -1$	$x_a = 0$	$x_a = 1$	ω	$x_a = -1$	$x_a = 0$	$x_a = 1$
$x_b = -1$	A	**B**	A	$x_b = -1$	B	B	B
$x_b = 0$	A	A	A	$x_b = 0$	**A**	B	**A**
$x_b = 1$	A	**B**	A	$x_b = 1$	B	B	B

4.3. **News selection and higher order beliefs.** Public signals that are commonly known to be observed by all agents are particularly influential when privately informed agents interact strategically(e.g. Morris and Shin 2002). Arguably, everything that is reported by newspapers is public in the sense that it is available for those who care to look for it. However, not all information that is printed in a newspaper is observed by everybody, and even when an event is widely reported, it may not be known to readers of all newspapers how widely reported it is. In the model above, when $\lambda \neq 0$, there are some states of the world in which Alice and Bob read about the same event and yet this event is not common knowledge.

To see this, consider first the case when Paper A reports about X_b. This only happens in the states $(0, 1)$ and $(0, -1)$ i.e. only in states of the world where Paper B also reports about X_b. This is natural since Alice has no direct interest in X_b and finds it useful to know about X_b only to the extent that it helps her predict the action of Bob. Because Alice understands that Bob will read about X_b for sure whenever she does, she knows not only that $X_b = x_b$ but also that Bob knows this as well. Yet, this fact is not common knowledge. Bob knows that he observes X_b in the states $(-1, 1), (1, 1), (-1, -1), (1, 1), (0, -1)$ and $(0, 1)$. But since Alice observes X_b only in the latter two states and because in these states, Bob attaches positive probability also to states where Alice does *not* observe X_b, the fact that $X_b = x_b$ is not common knowledge even though both Alice and Bob knows this to be true.[11]

The degree to which knowledge about an event is common among agents matter for agents optimal decision. As we will now demonstrate, the probability with which Bob believes that Alice observes X_b when he does affects not only how strongly he responds to the realized value x_b, but also how strongly Alice responds in those states of the world where she observes x_b.

[11]In fact, in the simple discrete example here, the only state in which any event is common knowledge is $(0, 0)$ since it is only in this state that Alice or Bob reads a report stating that the variable they have a direct interest in equals zero.

4.4. **Equilibrium actions.** Alice and Bob's equilibrium actions depend on the degree of strategic complementarities both directly through the first order condition (3.3) and through the effect that the strategic motive has on the equilibrium news selection functions. We now derive the optimal actions taking the news selection functions described by (4.3) or (4.4) as given.

4.4.1. *No strategic motive.* In the absence of a strategic motive, Alice always observes X_a and Bob always observes X_b. Alice and Bob's equilibrium actions are then trivially given by $y_a = x_a$ and $y_b = x_b$. Since X_a and X_b are independent random variables, Alice's and Bob's actions are also independent.

4.4.2. *Strategic motives in actions.* With a strategic motive, Alice sometimes observe X_b and Bob sometimes observe X_a. The optimal response to a news report depends on whether it is about a story that the agents have a direct or indirect interest in. We start by deriving the optimal action of Bob when he reads about X_a, i.e. the story that he has only an indirect interest in.

Bob knows that he only observes X_a when Alice does so as well. Bob can thus infer Alice's action with certainty when he observes X_a. Since Bob only observes X_a when $x_b = 0$, Bob's optimal action when he observes X_a is simply given by

$$y_b\left(x_a, \mathcal{S}_b = 0\right) = \lambda y_a\left(x_a, \mathcal{S}_a = 1\right). \tag{4.5}$$

When Alice observes X_a she does not know with certainty whether Bob does so as well. Her optimal action can then be expressed as

$$\begin{aligned} y_a\left(x_a, \mathcal{S}_a = 1\right) &= (1-\lambda)\, x_a \\ &\quad + p\left(\mathcal{S}_b = 0 \mid x_a, \mathcal{S}_a = 1\right) \lambda y_b\left(x_a, \mathcal{S}_b = 0\right) \\ &\quad + p\left(\mathcal{S}_b = 1 \mid x_a, \mathcal{S}_a = 1\right) \lambda E\left[y_b\left(x_b, \mathcal{S}_b = 1\right) \mid x_a, \mathcal{S}_a = 1, \mathcal{S}_b = 1\right]. \end{aligned} \tag{4.6}$$

Bob also observes $x_a \in \{-1, 1\}$ if $x_b = 0$ which happens with probability $\frac{1}{2}$. Because X_b is symmetrically distributed around zero, Alice's expectation of Bob's action when he observes X_b equals zero. Alice's optimal action when $x_a \in \{-1, 1\}$ can thus be simplified to

$$y_a\left(x_a, \mathcal{S}_a = 1\right) = (1-\lambda)\, x_a + \lambda \frac{1}{2} y_b\left(x_a, \mathcal{S}_b = 0\right). \tag{4.7}$$

Substituting (4.5) into (4.7) and switching to general indices gives the optimal actions as functions of the observed variables

$$y_i\left(x_i, \mathcal{S}_i = 1\right) = \frac{(1-\lambda)}{1-\frac{1}{2}\lambda^2} x_i \tag{4.8}$$

and

$$y_j\left(x_i, \mathcal{S}_j = 0\right) = \lambda \frac{(1-\lambda)}{1-\frac{1}{2}\lambda^2} x_i \tag{4.9}$$

We can see from (4.8) - (4.9) that the magnitude of both Alice and Bob's responses to x_a depends on the probability $p\left(\mathcal{S}_b = 0 \mid x_a, \mathcal{S}_a = 1\right)$. When Alice observes x_a, this is the probability she attaches to the event that Bob also observes x_a. When Bob observes x_a, this is the probability that Bob believes Alice attaches to the event that he observes x_a. Thus, the higher this probability is, the stronger is the response of both agents. The degree to which information about an event is common among agents thus affects the strength of the agents' responses, even when the event in question is mutual knowledge.

Incidentally, the expression (4.8) also describes the optimal action when agents observe that the variable they have a direct interest in equals zero. Since the agents only observe a zero realization in the state $(0, 0)$, and because this state is common knowledge, it is then optimal for both agents to take a zero action.

4.5. **Verifying the optimality of the conjectured news selection functions.** Given the optimal actions derived above, it is straightforward to verify by direct computation that neither Paper A nor Paper B has an incentive to deviate from the conjectured news selection functions described by (4.3). The Appendix describes an algorithm for doing so.

4.6. **Correlation of actions with and without delegated news selection.** To isolate the implications of the editorial function of the newspapers for agents' actions, we now compare the predictions of the model to a natural alternative. In the alternative model, Alice and Bob are, as in the benchmark model, restricted to observing only one out of the two realized events. However, instead of delegating the news selection to an information provider that can condition on ex post outcomes, Alice and Bob have to make a decision ex ante about which variable to observe.

When actions are strategic complements, that is, when $\lambda > 0$, Alice will then choose to always observe X_a and Bob will choose to always observe X_b. Alice and Bob will also chose to always observe the variable that they have a direct interest in when actions are strategic substitutes, as long as the strategic motive is not too strong.[12] Since X_a and X_b are independent, observing x_a is then uninformative about x_b and vice versa. The conditional expectation of the unobserved variable is then equal to its unconditional mean and the optimal action $\widetilde{y}_i$ with ex ante information choice is given by

$$\widetilde{y}_i = (1 - \lambda)\, x_i : i \in a, b \tag{4.10}$$

Clearly, if X_a and X_b are independent, Alice and Bob's actions $\widetilde{y}_a$ and $\widetilde{y}_b$ are uncorrelated in the alternative model.

Proposition 2. *Delegated news selection introduces correlation between Alice and Bob's actions of the same sign as λ.*

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

$$\frac{\sum_{\omega \in \Omega} p(\omega)\, y_a(\omega) y_b(\omega)}{\sqrt{var\,(y_a)}\sqrt{var\,(y_b)}} = \lambda \frac{2\,(1-\lambda)^2}{(2-\lambda^2)^2} var\,(y_i)^{-1} \tag{4.11}$$

where $y_i(\omega)$ is agent i's action in state ω. □

To see why the delegated news selection introduces correlation in the actions of the agents, first note that the terms in the sum of the left hand side of (4.11) associated with states where $x_a = x_b \in \{-1, 1\}$ cancel against the terms associated with the equally probable states where $x_a = -x_b \in \{-1, 1\}$. (The term associated with the state $(0, 0)$ is zero.) The

[12]The formal condition for Alice and Bob to choose to always observe the variable they have a direct interest in is that $\left(1 - \lambda^2\right)^2 + \lambda > 0$. The model with ex ante signal choice is derived and solved in the Appendix.

correlation in actions is thus driven by those states where both agents read about the same event. That is, in the states $(1, 0)$ and $(-1, 0)$ both Alice and Bob reads about X_a and in the states $(0, 1)$ and $(0, -1)$ they both read about X_b. The products of Alice and Bob's actions in these states are then either always positive if $\lambda > 0$ or negative if $\lambda < 0$. The editorial function of newspapers thus introduces correlation in agents actions that is absent if agents choose ex ante what variable to get information about. This correlation is positive if actions are strategic complements and negative if they are strategic substitutes.

The example with discrete states presented here can explain two of the features of the news coverage data that we documented in Section 2. First, the two newspapers cover different topics to different degrees on average. Second, in some states of the world, the two papers cover the same topic and the coverage then becomes more homogenous. The implication of this kind of delegated, state-dependent news selection is that agents can infer from what they observe how likely it is that the other agent observes the same information as he or she is. Through this channel, the news selection functions influence how strongly agents respond to a given news story. The strength of the responses of both agents is increasing in the probability that the agent with a direct interest in the story assigns to the event that the agent with only an indirect interest in the story also reads about it.

Because the two information providers sometimes choose to report on the same event, agents' actions are more correlated in the model with delegated news selection than they are in a setting in which agents choose ex ante what to get information about. The coordinating effect of news media identified in Proposition 2 works by affecting the actions of audiences across media outlets. In reality, most media outlets reach more than one agent. The correlation in actions introduced by the delegated news selection thus comes on top of any coordination of agents' actions that occur simply because a single news outlet may reach a large audience.

5. Extreme events and common knowledge

In the previous section we analyzed how delegated and state dependent news selection affects agents' beliefs and actions. We demonstrated that agents' preferences and the distribution of events influences the degree to which an event is commonly known. In the data, we saw that events such as the 9/11 terrorist attacks and the Lehman Brothers bankruptcy made news coverage more homogenous across news outlets. Arguably, what made these events special and so widely reported were their magnitudes, as both bank failures and terrorist attacks happen frequently on a smaller scale. The simple discrete state space set up above did not allow us to capture the notion of a large-magnitude event. In this section we therefore extend the analysis to allow for continuous distributions so that we can meaningfully study large-magnitude events.

5.1. **Optimal simple news selection functions.** With continuous distributions of the potential stories X_a and X_b, the optimal news selection functions are infinite dimensional objects with unknown functional forms. We therefore restrict the information providers to choose news selection functions from a simple parametric class of threshold functions in the absolute values of x_a and x_b of the form

$$\mathcal{S}_i = \begin{cases} 1 \text{ if } |x_i| \geq \alpha_i |x_j|^{\beta_i} \\ 0 \text{ otherwise} \end{cases} . \tag{5.1}$$

The function (5.1) is flexible and lets us represent a wide variety of news selection functions. Subject to this constraint on the functional form of their news selection function, Paper A chooses α_a and β_a in order to maximizes the expected utility of Alice and Paper B chooses α_b and β_b to do the same for Bob.

5.2. **Conditional actions.** When X_a and X_b are continuously distributed, the conditional expectations in the first order condition (3.3) can be expressed as

$$y_i(x_k, \mathcal{S}_i) = (1-\lambda) \frac{\int\int x_i p(x_i, x_j, \mathcal{S}_i) \, dx_i dx_j}{p(x_k, \mathcal{S}_i)} + \lambda \frac{\int\int y_j(x_i, x_j) \, p(x_i, x_j, \mathcal{S}_i) \, dx_i dx_j}{p(x_k, \mathcal{S}_i)}$$

where : $i, j, k \in \{a, b\}$ and $i \neq j$. For independent zero mean distributions of X_a and X_b, the news selection function (5.1) implies that the expected value of the unreported variable is the same as its unconditional mean.[13] As in the previous section, it is again optimal for Paper B to report about X_a only when Paper A does so as well. That is, if $\mathcal{S}_j = 0$, then $\mathcal{S}_i = 1$. Taken together, these two facts allow us to simplify the optimal action (**??**) to

$$y_i(x_i, \mathcal{S}_i = 1) = \frac{(1-\lambda)}{1 - p(\mathcal{S}_j = 0 \mid x_i, \mathcal{S}_i = 1) \lambda^2} x_i \tag{5.2}$$

and

$$y_i(x_j, \mathcal{S}_i = 0) = \lambda \frac{(1-\lambda)}{1 - p(\mathcal{S}_i = 0 \mid x_j, \mathcal{S}_j = 1) \lambda^2} x_j \tag{5.3}$$

As in the discrete states model above, the strength of agents' responses to news stories depends on the degree to which the observed event is common knowledge, i.e. the probability in the denominator of (5.2) and (5.3). Here, these probabilities vary smoothly with the realized value of the state and depend on the values of α_j and β_j. Because the optimal news selection functions depend on the strength of the strategic motive, the degree to which an event becomes common knowledge depends both on the realized value of X_a and X_b as well as on the preferences of Alice and Bob.

5.3. **Solving the model.** With continuous distributions, we need to solve the model numerically. A solution can be found by letting Paper A choose α_a and β_a in order to maximize Alice's utility, taking Bob's actions as given. Paper B then chooses α_b and β_b in order to maximize Bob's expected utility, taking Alice's actions from the previous step as given. Iterating between these two steps until convergence yields a solution.

[13]The conditional distribution $p(x_i \mid x_j, \mathcal{S}_i = 0)$ is simply $p(x_i)$ with symmetrically truncated tails.

5.4. **Preferences, distributions and common knowledge.** From the expressions (5.2) - (5.3) of the optimal action, we know that the strength of both Alice and Bob's responses to observing x_a depends on how likely Alice thinks it is that Bob also observes x_a. By Bayes' rule, this probability is given by

$$p\left(S_b = 0 \mid S_a = 1, x_a\right) = \frac{p\left(S_a = 1 \mid S_b = 0, x_a\right) p\left(S_b = 0 \mid x_a\right)}{p\left(S_a = 1 \mid x_a\right)} \tag{5.4}$$

Now, since Bob only observes X_a when Alice does so as well, we have that $p\left(S_a = 1 \mid S_b = 0, x_a\right) = 1$ so that (5.4) simplifies to

$$p\left(S_b = 0 \mid S_a = 1, x_a\right) = \frac{p\left(S_b = 0 \mid x_a\right)}{p\left(S_a = 1 \mid x_a\right)}. \tag{5.5}$$

With delegated information choice, the degree to which information about a realized event is common among agents depend on agents' preferences as well as on the distributions of events. To illustrate how these interact, we here solve the model for different values of λ and for different distributions of X_a and X_b. For each set up we compute the conditional probability that Alice and/or Bob observes X_a as a function of its realized value.

Figure 5 illustrates the probabilities that Alice and/or Bob observes X_i or X_j as a function of the realized value of X_i and the strength of the strategic motive. The left column corresponds to $X_i \sim U(-1, 1)$ and the right column to $X_i \sim N(0, \frac{1}{3})$, illustrated by the dotted blue lines. To facilitate comparison, the variance of the Gaussian distribution is chosen so that most of its probability mass lies within the support of the uniform distribution.

5.4.1. *No strategic motive.* The first row of Figure 5 illustrates the probability that Alice (solid red) and Bob (dashed yellow) observe X_a conditional on the realized value x_a when $\lambda = 0$. As in the discrete state case, Alice always observes X_a and Bob never observes X_a so for all values of X_a the associated conditional probabilities are 1 and 0 respectively. The optimal news selection functions are symmetric across the papers and given by $\alpha_i = 0$ (and an indeterminate β_i).

5.4.2. *Moderate strategic motive.* When $\lambda = 0.3$, the optimal news selection functions are symmetric and characterized by α_i approximately equal to 0.3 and β_i equal to 1. Reflecting the direct interests of their respective readers, Paper A will then report about X_a most of the time and Paper B will report about X_b most of the time. However, when $|x_a|$ is sufficiently large relative to $|x_b|$, that is when $0.3 \times |x_a| > |x_b|$, both papers will report about X_a. This is so because Alice will take an action that is large in absolute terms and it is then more important for Bob to know about Alice's action than about the small (in absolute terms) realized value of X_b. Ceteris paribus, both Alice and Bob's expected losses of not knowing about x_a is thus increasing in the absolute realized value of X_a.

The middle row of Figure 5 shows that the probability that Alice observes X_a increases rapidly as the absolute value of x_a increases for both the uniform and the normal distribution. The probability that Bob observes X_a is also increasing in $|x_a|$. Since the states in which Bob observes X_a is a strict subset of the states where Alice observes X_a, Bob's probability of observing X_a is lower than the probability that Alice does so for every value of x_a.

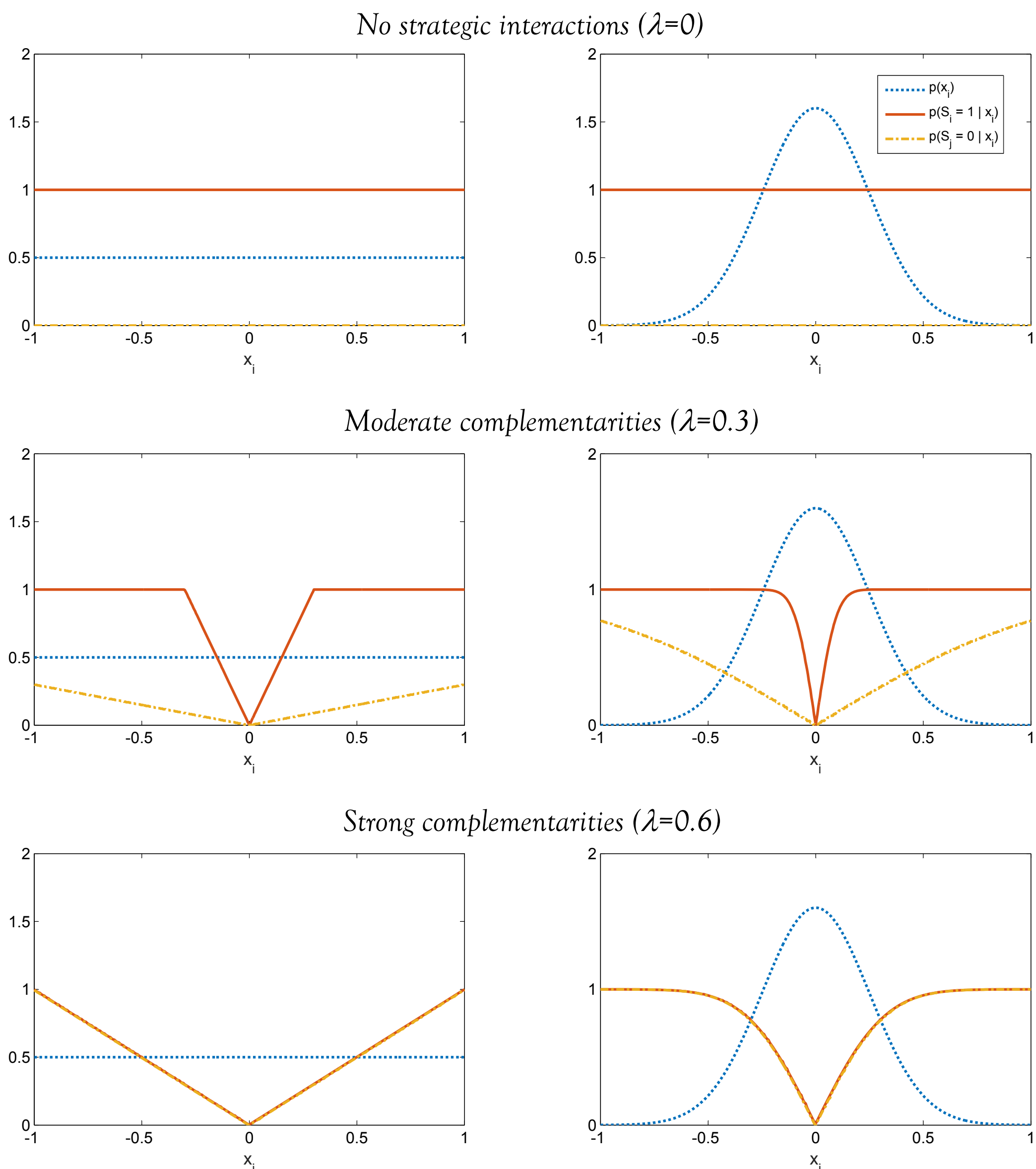


FIGURE 5. The probability that the agent i (solid red) and agent j (yellow dashed) observe x_i conditional on x_i with X_i and X_j distributed as $U(-1,1)$ (left column) and $N(0,1/3)$ (right column). Top row is model without strategic motive ($\lambda = 0$), middle row with moderate strategic motive ($\lambda = 0.3$) and bottom row with strong strategic motive ($\lambda = 0.6$).

The probability (5.5) that Bob observes x_a conditional on Alice doing so corresponds to the ratio of the (dashed) yellow and (solid) red lines in the graph. Alice knows that Bob is more likely to observe X_a as the absolute value of x_a increases, so larger magnitude events tend to be closer to common knowledge. For the uniform distribution, Alice attaches about a 30 per cent probability to the event that Bob observes X_a when X_a is close to -1 or 1. When the events are normally distributed, the same probability is about 75 per cent. The difference between the uniform and the normal distributions is explained by the fact that with normally distributed variables, the probability mass is more concentrated around the means, so conditional on the realized value of X_a, it is then less likely that the realized (absolute) value of X_b is large enough to make Paper B report x_b instead of x_a. With normally distributed variables and for a large enough absolute realization of X_a, both Paper A and Paper B report x_a almost surely. In the limit, information about extreme realizations of x_a or x_b thus approaches common knowledge.

5.4.3. *Strong strategic motive.* As the strategic motive is strengthened the cost of not observing the event that the other agent is responding to increases. The news selection functions of the two papers then become more similar. When $\lambda = 0.6$ (bottom row of Figure 5) both Paper A and Paper B will simply report the variable that has had the largest absolute realization and $\alpha_i = \beta_i = 1$ for both Paper A and Paper B. Since the news selection functions are known to both agents, Alice can then infer that if she observes X_a then $|x_a| > |x_b|$ so that Paper B will also report X_a. With sufficiently strong complementarities in actions, both papers will always report the same event and the reported event will be common knowledge. Effectively, the model then functions as if there was a single information provider. The realized values X_a and X_b are then either common knowledge or not known to any agent.

5.5. **News Selection and Aggregate Actions.** Ultimately, we are interested in how the delegated information choice affects agents' actions. The news selection functions affect agents' actions through two distinct channels. First, the news selection functions determine how likely it is that an agent knows about an event. If an agent does not know that an event has occurred, he or she cannot respond to it. Second, conditional on reading about an event, the news selection functions affect how likely it is that the other agent is reading about the same event. When actions are strategic complements, an agent will respond more strongly to an event if he thinks it is more likely that the other agent also observes the same event.

As we saw in Figure 5 above, the probability that the two agents observe an event x_i is increasing in its absolute realized value. Figure 6 illustrates how these probabilities translate into expected aggregate actions for different values of λ and for different distributions of X_a and X_b.

When $\lambda = 0$, Alice always observes X_a, but Bob never does. The probability in the denominator of (5.2) and (5.3) is then zero, and Alice's response is linear in x_a. Because Bob never observes X_a, the conditional expectation of his action is zero for all values of x_a. The conditional expectation of the aggregate action illustrated by the dotted grey line is thus simply Alice's expected action. When $\lambda > 0$, the probability that Bob and/or Alice observes X_a increases in the absolute value of x_a, and so does the probability that Bob observes x_a conditional on Alice doing so. These effects introduce a nonlinearity in the expected aggregate response, as illustrated by the dashed grey and solid blue lines in Figure 6.

To understand the source of this non-linearity, consider first realizations of X_a that are close to zero. In the zero limit, the probability that Alice or Bob observe X_a is also zero, and then so is the conditional expectation of the sum of their actions. The expected response curve in the Figure 6 is therefore flat around the point where $x_a = 0$. As the absolute value

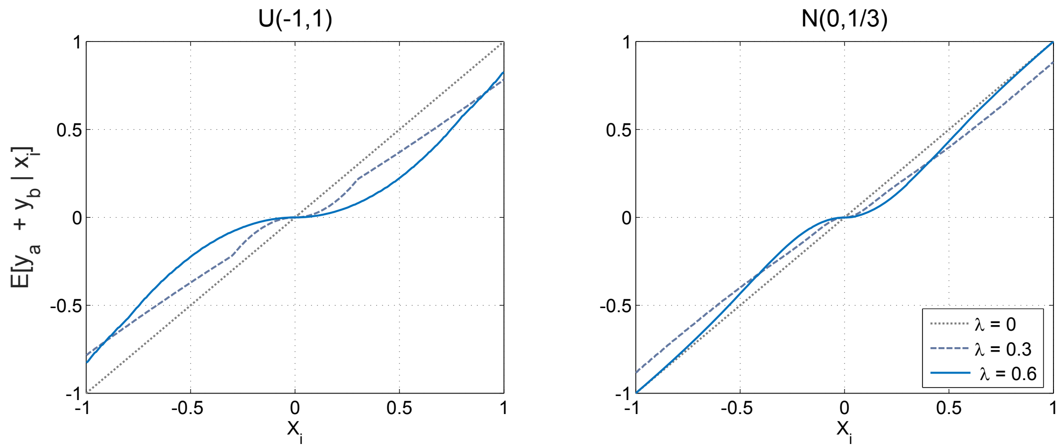


FIGURE 6. Expected aggregate response conditional on x_i with $U(-1,1)$ (left panel) and $N(0, \frac{1}{3})$ (right panel) distributions of X_i and X_j.

of x_a increases, the probability that Alice and Bob reads about it increases. Now, both the probability that the agents read about X_a and the degree to which this fact is common knowledge is increasing in $|x_a|$. The magnitude of the expected aggregate response to x_a is thus increasing more than proportionally in $|x_a|$.

The mechanism thus generates weak responses to small magnitude events, and comparably strong responses to large magnitude events. The model here thus captures how events compete for media coverage. Small magnitude events only become widely known if no competing more extreme event has occurred. But because agents generally will not be able to infer that the minor event is in fact widely reported, the resulting responses are weaker. More extreme events however, are not only more likely to be widely reported, but because they also tend to be closer to common knowledge, agents' responses to such events are stronger.[14]

6. Conclusions

News media are an important source of information for a large part of society. In this paper we have argued that in order to understand how news media affect decisions, we need to first understand how they select what stories to report. We therefore obtained text fragments from a large number of news stories published in US newspapers during the months around the September 11 terrorist attacks and the Lehman bankruptcy in 2008. We then used a Latent Dirichlet Allocation topic model to document three stylized facts about news coverage. First, different newspapers provide specialized content and tend to cover different topics to different degrees. Second, major events such as terrorist attacks or financial crises result in a large fraction of news content being devoted to the topics associated with these events. Third, major events make news coverage more homogenous across newspapers.

[14]In this section, we analyzed the effect of news selection when $\lambda \geqslant 0$. Results are qualitatively unchanged if we allow for actions to be strategic substitutes. Additional results pertaining to the cases when $\lambda < 0$ are reported in the Online Appendix.

To interpret these findings and to analyze their implications, we proposed a simple beauty-contest model that can replicate the documented facts. The model is populated by agents that have heterogeneous interests and delegate their decisions of what to get information about to specialized news providers that cater to their specific interests. These news providers perform an editorial service for the agents by monitoring the entire state of world and by choosing ex post which of the realized events to report. This mechanism of delegated information choice generates new predictions relative to models where agents choose what to get information about based on the ex ante expected usefulness of different signals. In our set up, what *has happened* affects what agents get information about. Because of this, the model can match the stylized facts about news coverage documented in the first part of the paper.

We formalized the editorial decision of news media as a mapping between states of the world and a selection of reported events. Because this selection is systematic, and understood by the agents, the selection of reported events is by itself potentially informative also about non-reported events. One contribution of the paper is to provide formal conditions for when this is the case. The systematic selection of reported events also makes it possible for agents to infer how likely it is that other agents read about he same event as they are. When agents have a strategic motive, they respond stronger to events that they can infer that other agents are more likely to know about as well. Thus, in order to predict how the economy will respond to a given event, we must first understand how common information about the event is among agents.

In the model, the degree to which information about an event is common among agents is endogenous, and depends on the agents' preferences, the event itself and the distribution of possible events. In the mode, information about most events is neither perfectly public nor perfectly private. This contrasts with the large literature that has studied the role of private and public information in strategic settings, e.g. Morris and Shin (2002) and Angeletos and Pavan (2007). In this literature, signals are either perfectly private or perfectly public and this structure is unaffected by preferences and the realized state of world. Here, we break this clean dichotomy and make positive predictions about the types of environments and events to which the results of this existing literature are most likely to apply.

We also demonstrated that delegated and state-dependent information choice can introduce correlation between agents' actions compared to a setting in which agents choose ex-ante what to get information about. That the editorial role of information providers facilitates coordination in some states of the world has implications for the large existing literature proposing that business cycles are (at least partly) caused by agents coordinating on either pure sun-spot shocks, e.g. Cass and Shell (1983), on noisy public signals e.g. Lorenzoni (2009) and Nimark (2014), or on "sentiment" shocks e.g. Angeletos and La'O (2013). One feature these papers have in common is that the coordination of actions cannot rely solely on the information that is transmitted through prices. The argument we make in this paper is that, to the extent that coordination works via news media, coordination will be facilitated in those states of the world in which news coverage is more uniform across different news providers.

Finally, in the theoretical model above, we take a very benevolent view of news media and assume that reporting is unbiased. However, the mechanisms that we highlight do not rely on this assumption and arise as long as potential biases are systematic and understood by the agents in the model. For instance, if newspapers are more likely to report bad news events relative to good ones, negative events will be closer to common knowledge and provoke stronger responses than good events of similar magnitude.

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Appendix A. Verifying equilibrium in news selection functions

Define $y_i(\omega)$ as the optimal action associated with state $\omega \in \Omega$ for agent i. A news selection function $\mathcal{S}_i(\omega)$ determines whether agent i observes x_a or x_b. The optimal action when agent i observes x_k and $\mathcal{S}_i$ can be expressed as

$$y_i(x_k, \mathcal{S}_i) = (1-\lambda)\frac{\sum x_i p(x_i, x_k, \mathcal{S}_i)}{p(x_k, \mathcal{S}_i)} + \lambda \frac{\sum y_j p(y_j, x_k, \mathcal{S}_i)}{p(x_k, \mathcal{S}_i)} \tag{A.1}$$

The news selection function is defined by a binary choice in each of the $3 \times 3 = 9$ states of the world, implying that there are $2^9 = 512$ different news selection functions for each information provider. The conjectured news selection functions in Section 3 can be verified to be a Nash equilibrium as follows.

1. For each possible news selection function for $\mathcal{S}_a$
   - (a) Find Alice's optimal actions in each state of the world as described by (A.1) taking Bob's action in each state as given.
   - (b) Given Alice's actions computed in Step ($1a$) and the conjectured news selection function $\mathcal{S}_b$, compute Bob's optimal action as described by (A.1).

(c) Iterate on steps ($1a$) and ($1b$) until both Alice and Bob's actions have converged.
(d) Compute expected utility of Alice and save.

If Alice's maximum expected utility in Step 1d coincides with the expected utility in the conjectured equilibrium, Paper A has no incentive to deviate. Because of symmetry, Paper B then also do not have an incentive to deviate and the conjectured news selections functions an equilibrium.

Appendix B. Alternative model with ex ante information choice

Here we derive the solution to the alternative model discussed in Section 4 of the paper. The set up is identical to the benchmark model except that agents choose ex ante which story to get information about.

B.1. **Optimal action.** As in the benchmark model, the optimal action $\widetilde{y}_i$ of agent i is described by the first order condition

$$\widetilde{y}_i = (1-\lambda) E_i [x_i] + \lambda E_i [y_j] : i \neq j \tag{B.1}$$

where E_i is the expectations operator conditional on agent i's information set.

B.2. **Information choice.** Define the utility of agent i when she observes X_j as $U_i (X_j)$. Agents choose ex ante whether to observe X_a or X_b and agent i will choose to observe X_i when the expected utility of doing so is higher than the expected utility of observing X_j. To solve for the information choice, we thus need to find expressions for the expected utility under the two choices.

B.2.1. *Alice and Bob observe different stories.* If agent i observes x_i and agent j observes x_j their respective actions are

$$\widetilde{y}_i = (1-\lambda) x_i, \quad \widetilde{y}_j = (1-\lambda) x_j.$$

Agent i's expected utility when she observes X_i is then given by

$$EU_i(X_i) = -(1-\lambda) E [(1-\lambda) x_i - x_i]^2 - \lambda E [(1-\lambda)(x_i - x_j)]^2 \tag{B.2}$$

or

$$EU_i(X_i) = -(1-\lambda) \lambda^2 E x_i^2 - \lambda (1-\lambda)^2 E (x_i - x_j)^2 \tag{B.3}$$

B.2.2. *Alice and Bob observe the same story.* When both agents choose to observe X_j the actions are given by

$$\widetilde{y}_i = \lambda \frac{1-\lambda}{1-\lambda^2} x_j, \quad \widetilde{y}_j = \frac{1-\lambda}{1-\lambda^2} x_j$$

The expected utility of agent i then is

$$EU_i(X_j) = -(1-\lambda) E \left[\lambda \frac{1-\lambda}{1-\lambda^2} x_j - x_i\right]^2 - \lambda E \left[\lambda \frac{1-\lambda}{1-\lambda^2} x_j - \frac{1-\lambda}{1-\lambda^2} x_j\right]^2 \tag{B.4}$$

which can be rearranged to

$$EU_i(X_j) = -(1-\lambda) E \left[\lambda \frac{1-\lambda}{1-\lambda^2} x_j - x_i\right]^2 - \lambda E \left[\frac{(1-\lambda)(\lambda-1)}{1-\lambda^2} x_j\right]^2 \tag{B.5}$$

and simplified to

$$EU_i(X_j) = -(1-\lambda)\lambda^2 \frac{(1-\lambda)^2}{(1-\lambda^2)^2} Ex_j^2 - (1-\lambda) Ex_i^2 - \lambda \left(\frac{(1-\lambda)(\lambda-1)}{1-\lambda^2} \right)^2 Ex_j^2 \quad \text{(B.6)}$$

B.2.3. *Solving for the information choice.* Without loss of generality, we can normalize the variances of X_i and X_j to 1. The expected utilities can then be written as

$$EU_i(X_i) = -(1-\lambda)\lambda^2 - \lambda 2 (1-\lambda)^2 \quad \text{(B.7)}$$

and

$$EU_i(X_j) = -(1-\lambda)\lambda^2 \frac{(1-\lambda)^2}{(1-\lambda^2)^2} - (1-\lambda) - \lambda \frac{(1-\lambda)^2 (\lambda-1)^2}{(1-\lambda^2)^2} \quad \text{(B.8)}$$

Agent i will choose to observe X_i when $EU_i(X_i) > EU_i(X_j)$, that is, when the inequality

$$-(1-\lambda)\lambda^2 - \lambda 2(1-\lambda)^2 > -(1-\lambda)\lambda^2 \frac{(1-\lambda)^2}{(1-\lambda^2)^2} - (1-\lambda) - \lambda(\lambda-1)^2 \frac{(1-\lambda)^2}{(1-\lambda^2)^2} \quad \text{(B.9)}$$

holds. Move all terms in (B.9) to the left hand side and divide by $(1-\lambda)$ to get

$$-\lambda^2 - \lambda 2(1-\lambda) + 1 + \lambda^2 \frac{(1-\lambda)^2}{(1-\lambda^2)^2} + \lambda(\lambda-1)^2 \frac{(1-\lambda)}{(1-\lambda^2)^2} > 0. \quad \text{(B.10)}$$

The resulting inequality can then be simplified to

$$\left(1-\lambda^2\right)^2 + \lambda > 0 \quad \text{(B.11)}$$

The inequality (B.11) holds for all $\lambda > 0$. Alice will thus choose to always observe X_a when actions are strategic complements, and Bob will then also choose to always observe X_b. When actions are strong enough strategic substitutes, agents will choose to coordinate so that they both always observe either X_a or X_b. While there is no simple analytical solution to (B.11), solving (B.11) numerically shows that agents will choose to observe the same variable when $\lambda \in (-1, -0.53)$.