What's on the news?
Mass media and persistent slumps

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Abstract

In this paper, I document that mass media become more coordinated in economic reporting when the economy is in a recession. I present a model that incorporates time-varying imperfect common knowledge to study the role of mass media in generating persistent economic slumps. As newspapers become more coordinated, economic conditions become increasingly more common knowledge among firms. During a recession, the decision of firms not to invest is amplified because they are aware that other firms are also not willing to invest. As a result, mass media contribute in turning an otherwise mild recession into a persistent slump.

(Preliminary and Incomplete)

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1 Introduction

In this paper, I document that mass media become more coordinated when the economy is in a recession. This new stylized fact about economic reporting highlights the importance of fluctuations in imperfect common knowledge for the business cycle. The response of the economy to a shock is affected by the degree to which it is perceived by agents in the economy (Woodford, 2001). If negative shocks are associated to higher degrees of common knowledge, the economy will naturally react more to a negative shock than to a positive shock of the same magnitude. In this setup, variations in common knowledge along the business cycle can create an asymmetry in the reaction of the economy to shocks. This asymmetry can be used to explain unprecedented slow recovery from the Great Recession.

In order to show that economic conditions become more common knowledge during recessions, I apply Latent Dirichlet Allocation (LDA) to uncover a structure of 40 topics discussed in the front page of newspapers published in the US between 2007 and 2011. Five of these topics are related to economic issues, ranging from the stock market to the European Debt Crisis. I find that the correlation between newspapers of economic content – defined as the proportion of economics-related topics in the front page of a given day – increases during recessions. In addition, economic content also becomes more similar. This evidence suggests that people become more aware of economic conditions during recessions. This observation gives mass media a central role in the business cycle. Mass media are a potentially key element to explain variations of common knowledge.

Motivated by this evidence, I present a framework to explain the contribution of mass media in generating persistent economic downturns. I build a model of investment based on the global games literature (Morris and Shin, 2000b) to which I introduce a dynamic component. As a result, the model features non-linear dynamics in the form of multiple steady states that can lead to persistent recessions. The global game approach guarantees uniqueness of equilibrium. Because the framework allows for a clear distinction between multiplicity of equilibria and steady states, a secondary contribution of this paper is to highlight the different forces behind both phenomena.

The approach I follow allows me to isolate the role of time-varying common knowledge from the effects of uncertainty. In this framework, I model mass media as a public signal structure with correlated noise. The more correlated is the noise between different sources, the more common knowledge there is in the economy. More importantly, a higher correlation will provide more information about what other people know. However, it will give no additional information about the value of fundamental. This modeling strategy will also be useful for the quantitative section. Correlation of noise between signals finds its real counterpart in the correlation of economic content measured in the empirical analysis.

In this setup, as mass media become more coordinated, economic conditions become more common knowledge among firms. During a recession, the decision of firms not to invest is amplified because they are aware that other firms are also not willing to invest. Mass media then contribute to the business cycle by increasing awareness of the economic conditions. This increase in common knowledge can turn an otherwise mild recession into a persistent slump.

The global games approach is particularly suited to formalize the contribution of media to economic slumps. The reason is that this framework can embed the key elements needed to formalize this idea. First, a binary investment decision that generates sufficient non-linearities to allow for multiple steady states. Second, a set of public signals, which act as a coordination device for agents' beliefs about the state of the economy. Third, complementary decisions. Together with the public signals, complementarities ensure that correlation in beliefs translate into correlated actions. With agents acting all at once, the economy can suffer from small perturbations to the fundamental when it is "close to the edge" between two steady states. Finally, persistent investment dynamics impede a quick rebound to the initial state of the economy.

To asses the quantitative relevance of the mechanism, I embed the signal structure of the newspaper into the model developed in Schaal and Taschereau-Dumouchel (2015). The model is a standard real business cycle model with monopolistic producers in which firms choose capacity utilization under uncertainty about a fundamental process. It features demand complementarities as firms' individual production decisions are done taking into account aggregate demand. In addition, firms' capacity utilization provides a strong feedback between aggregate demand and production decisions. The combination of these two features gives rise to multiple equilibria, which are disciplined using a global game approach. In equilibrium, the final good behaves as if it were produced by a representative firm with an endogenous, non-linear component.

In a simulated version of the model, aggregate TFP in the model is bimodal because of its non-linear behavior. This feature is then reflected in aggregate variables. In addition, the simulated aggregate variables are negatively skewed, as the economy goes through phases of low activity. These are two features of the data that standard business cycles are not able to replicate.

Literature Review

The primary contribution of this paper is the proposal of a new mechanism by which variations in common knowledge can generate persistent recessions. This contribution is embedded in the recent literature of business cycles with dispersed information. The removal of the common knowledge assumption can help accommodate, for example, the notion of animal spirits that mainstream models cannot (e.g. Angeletos and La'O (2013); and Benhabib et al. (2015)).

The closest paper within this class is Nimark (2014), which investigates the business cycle implications of a key aspect of news reporting: the fact that unusual events are more likely to be reported than commonplace ones (referred to as "man-bites-dog" signals). In particular, Bayesian agents updating to signals that are more likely to be available about unusual events can explain large changes in aggregate variables without an easily identifiable change in fundamentals.

This paper shares some similarities with the news shocks literature (Beaudry and Portier (2004); Jaimovich and Rebelo (2009); and Lorenzoni (2009)). In this literature, business cycles are driven by difficulties encountered by agents in properly forecasting future productivity. I model instead news about the economy as a set of public signals with correlated noise. Productivity is still the main driver of the business cycle.

This paper also shares some similarities with the uncertainty shocks literature (Bloom (2009); Bloom et al. (2018)).[1] This literature posits that business cycle fluctuation can be accounted by variations in the standard deviation of the shocks that hit the economy (Fernandez-Villaverde and Guerron-Quintana (2020)). I highlight the role of uncertainty about what others know, instead of uncertainty about the fundamental.

By applying this framework to media, I also contribute to the literature studying its economic impact. Mass media are known to have an impact on policy outcomes (Strömberg (2004); Besley and Burgess (2002); Eisensee and Strömberg (2007)), asset prices (Tetlock, 2007) and economic expectations (Boomgaarden et al., 2011). However, there are few attempts to incorporate mass media into business cycle models. Chahrour et al. (2019) is a notable example. The authors show that media reporting about unrepresentative sectors of the economy coordinates firms' labor decisions. This creates the appearance of aggregate shocks orthogonal to productivity, even though the only source of exogenous variation are sector-specific shocks.

The presence of public information generates instability in the form of transitions between steady states. Previous literature has emphasized the detrimental effects of information. Morris and Shin (2002) explore the dual role of public

[1]See Fernandez-Villaverde and Guerron-Quintana (2020) for a review on the literature.

noise both as provider of information about the fundamental and as a coordination device. In setups with private information, excessive weight on the public signal can induce to an excess of coordination, which can lead to higher volatility and lower welfare. This result is generalized in Angeletos and Pavan (2007). In a more applied setting, Angeletos et al. (2016) find that information can be welfare-deteriorating if the cycle is driven by distortionary (e.g. markup) shocks.

The modeling approach in this paper draws from the global games literature (Carlsson and van Damme (1993); Morris and Shin (1998)). In particular, I solve a dynamic version of the global game with public information present in Morris and Shin (2000b). As in Steiner (2008), the dynamic link between periods leads to endogenous cycles in the equilibrium cutoff. Finally, Edmond (2013) applies global games to political regime changes with manipulated media. He also highlights the importance of the regime's manipulation being common knowledge.

Global games have been used in the business cycle literature to discipline equilibrium selection in models with strong complementarities. Schaal and Taschereau-Dumouchel (2015) propose a theory of coordination failures driven by demand complementarities. I embed the signal structure in their model for the quantitative exercise.

2 Economic Reporting in the United States

In this section, I document that recessions are accompanied by an increase in the degree of common knowledge about the economic situation. In particular, I use machine learning techniques to uncover the amount of economic content in the front page of newspapers. Economic content not only increases during recessions, it also becomes more coordinated and homogeneous among different newspapers.

2.1 Newspaper Data

The empirical analysis of this paper focuses on the period around the Great Recession going from January 2007 to December 2011. I use data from the Dow Jones Factiva database, which contains textual content from more than 30,000 sources.

Within the universe of content published in the US during that period, I limit the sample to front page articles and cover stories published by four newspapers: USA Today, the Washington Post, the Wall Street Journal and the New York Times.[2] Short articles, corrections and recurring sections are also excluded.[3] The sample amounts to a total of 29,042 articles. From each of these, I use the headline and the lead paragraph. Table 1 provides an illustration of the article database.

2.2 Latent Dirichlet Allocation

Introduced in Blei et al. (2003), the Latent Dirichlet Allocation (LDA) is an unsupervised topic model that treats each document as a mixture of topics, and each topic as a cluster of words. Given a set of documents, the LDA model recovers the underlying topic structure.

Several properties of the LDA model make it particularly useful in the context of newspaper articles. First, due to its unsupervised nature, the model recovers the underlying topic structure from the data without any prior assumption about the topics. Second, because documents are defined as a mixture, they are not restricted to a single topic. For example, the LDA will find that the first snippet from Table 1 discusses two different topics: firm management and security. Finally, the decomposition of documents into a numerical vector provides an

[2] Factiva's search engine tags each piece according to their own taxonomy (see Jones). In this case, the articles selected are the ones tagged with code NPAG, corresponding to "Page One Stories".

[3] That is, articles tagged with codes NCRX, NCDig and NSUM; corresponding to corrected items, corporate and news digests, respectively.

Text Snippet	**Publication**	**Date**
Barclays in Sanctions Bust – U.K. Firm to Pay $298 Million to Settle Charges Involving Iran. Barclays PLC agreed to pay 298 million to settle charges by U.S. and New York prosecutors that the U.K. bank altered financial records for more than a decade...	The Wall Street Journal	17/08/10
Denmark's 'flexicurity' blends welfare state, economic growth. Across Europe, nations such as France, Italy and Germany struggle with lackluster economic growth, high unemployment and high taxes...	USA Today	07/03/07
Iraq's turbulent effort to reckon with the violence of its past took another macabre turn on Monday when the execution of Saddam Hussein's half brother ended with...	The New York Times	16/01/07
Job Losses Worst Since '74: 533.000 Shed in November. The U.S. lost half a million jobs in November, the largest one-month drop since 1974, as employers brace for a recession...	The Wall Street Journal	06/12/08

Table 1: Sample text from the newspaper database.

easy way to compare articles between each other. This decomposition will be the basis to

Although the use of LDA models in economics is not as prevalent as in other fields, there are notable exceptions. Recently, Hansen et al. (2018) have used this method to analyze FOMC transcripts. Similarly, research at the Norges Bank has applied LDA to predict households' inflation expectations (Larsen et al., 2019) and to quantify narratives relevant to the business cycle (Larsen and Thorsrud, 2018).

The LDA model works as follows.[4] Consider a set of D documents, each of length N_d, with an associated vocabulary list of size N. In the LDA framework, each document d is assumed to be generated as a mixture over a set of K latent topics. The latent structure of the model is given by the matrix of topic-document proportions, $\boldsymbol{\theta}$; the distribution of words over topic, $\boldsymbol{\beta}$; and the matrix assigning each word to a topic $\boldsymbol{z}$. The purpose of the LDA model is to recover this underlying structure using only the set of words $\boldsymbol{w}$. Figure 1 synthesizes the structure of the model in a simple diagram.

Given the set of words $\boldsymbol{w}$, the joint distribution of $\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{z}$ can be approximated by

$$Pr\left(\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{z} \,|\, \boldsymbol{w}\right) \propto \prod_{d=1}^{D} P\left(\theta_d\right) \prod_{k=1}^{K} P\left(\beta_k\right) \left(\prod_{n=1}^{N_d} P\left(w_{dn} \,|\, z_{dn}, \boldsymbol{\beta}\right) P\left(z_{dn} \,|\, \theta_d\right) \right) \quad (1)$$

where each column of the $D \times K$ matrix $\boldsymbol{\theta}$ is the topic proportion for document d, and each row of the $K \times N$ matrix $\boldsymbol{\beta}$ is the word distribution for topic k. The assignment to a topic of a word n in document d is given by z_{dn}.

Maximizing the expression (1) in order to estimate the underlying structure of the model requires advanced computational techniques. Fortunately, there are several routines available that implement the LDA. In what follows, I apply the Gibbs sampling algorithm developed by McCallum (2002) for the choice of

[4]See Blei and Lafferty (2009) for a more detailed exposition of the LDA model.

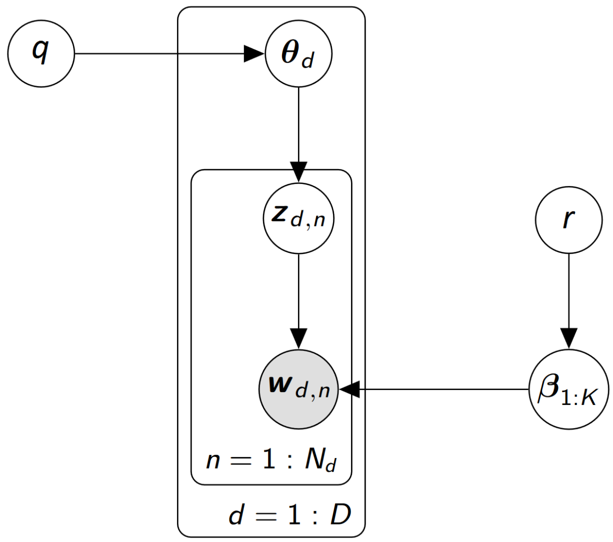

Figure 1: Plate Diagram of the Latent Dirichlet Allocation. Source: Blei et al. (2003).

$K = 40$ topics.[5] I apply the LDA at the front page level. That is, I define a document d as the union of articles published during the same day by a given newspaper.

2.3 Results of the LDA

The LDA produces two outputs of interest; the distribution of words per topic $\boldsymbol{\beta}$, and the distribution of topics per article $\boldsymbol{\theta}$. The first can be used to give an interpretation to the topics. Some topics are easy to interpret by looking at its high-probability words. Other topics require a closer inspection to their most representative articles. Figure 2 presents a word cloud of the highest probability words for the economics-related topics, together with its label.[6]

[5] Details about the choice of the number of topics and text preprocessing are described in Appendix A.1 and A.2.

[6] For the remaining topics, see Tables 4 and 5 in Appendix A.3.

Figure 2: Word cloud of the economics-related topics. Each word cloud includes the highest-probability terms, its size weighted by their probability.

The topics discussed within the category of economics are related to the stock and the mortgage market (topics 5 and 16), the release of economic reports and forecasts (topic 29), the announcement of financial stimulus (topic 27), and the European Debt Crisis (topic 31). Non-economics related topics fit into five broad categories: politics, war, international, science & environment, sectoral news and soft news.[7]

The second output of the LDA is the distribution of topics per article $\boldsymbol{\theta}$. Each element θ_{dk} corresponds to the proportion of topic k in article d. Figure 3 plots the daily topic proportion of the six economics-related topics. The an-

[7]Sectoral news include news without economic content about different sectors such as health or education (topics 17 and 38). The term soft news refers to human-interest stories and commodity news (e.g. sports or entertainment).

nouncement of financial stimulus is the most prevalent topic during the sample. The banking system topic peaks during October 2008, coinciding with the bankruptcy of Lehman Brothers. Discussion about the European debt crisis initially peaks around May 2010, coinciding with the announcement of the first bailout to Greece. The topic proportion then increases steadily, closely following talks about a second bailout.

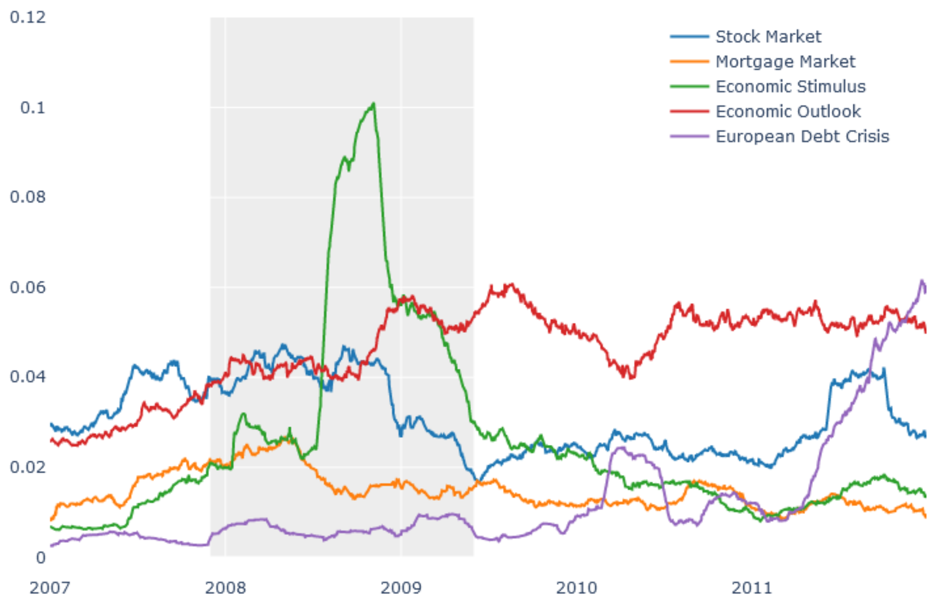

Figure 3: Mean topic proportion per day for the economic-related topics. The gray shaded area indicates a recession as defined by the NBER. The series have been smoothed with a two-sided rolling window of 4 months for illustrative purposes.

2.4 Measuring Economic Content

In order to show that newspapers coordinate in the way they report about the economy during recessions, I first need to define the economic content of the front page, d. In what follows, I denote the economic content of the front page as the sum of the proportion of economics-related topics. That is,

$$EconCont_d = \sum_{k \in Econ} \theta_{dk} \tag{2}$$

for all topics k belonging to the economics category. For example, the fourth article from Table 1 has an 86% of economic content, attributable almost entirely to the Economic Outlook topic.[8] On the other hand, the second article has a 81% of economic content distributed between three different topics: Economic Stimulus, the European Debt Crisis and Economic Outlook.

Figure 4 plots the evolution of economic content in the front page for every newspaper. Economic content increases in the beginning of the recession and peaks around October 2008, coinciding with the bankruptcy of Lehman Brothers. From then on, it decreases to a higher level than prior to the recession. The Wall Street Journal is the newspaper with a higher economic content, followed by USA Today.

During the Great Recession newspapers not only increased their economic content, they did so in a more coordinated manner. Figure 5 plots the correlation of the measure (2) between all pairs of newspapers. Correlation in economic content also reaches its maximum around October 2008. To show more formally the relationship between the correlation of economic content and the business cycle, I estimate the following model,

$$Corr_{it} = \beta_0 + \beta_1 Recess_t + f_i + u_{it} \tag{3}$$

where $Corr_{it}$ is the correlation of economic content at day t for a newspaper pair i, $Recess_t$ is a dummy which equal to one if the economy was in a recession at day t, f_i are newspaper-pairs fixed effects and u_{it} is the error term. Column (1) of Table 2.4 presents the results of the estimated model (3). Correlation of economic content during economic expansions averages to 0.1, and to 0.26 during recessions. The difference is statistically significant at the 1% level. Although these results do not necessarily speak about causality, they show that

[8] See Table ?? for more details about the topic proportions of articles in Table 1.

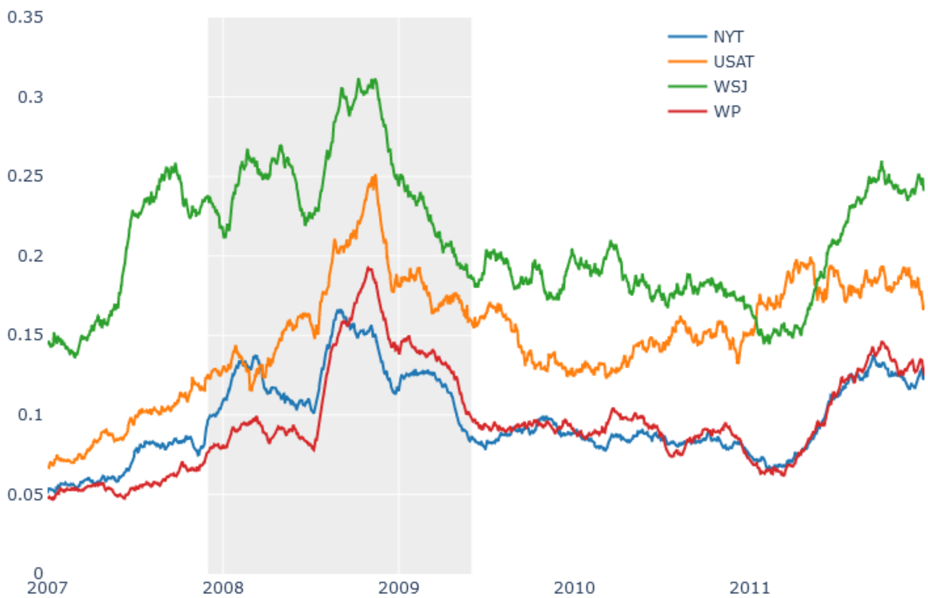

Figure 4: Daily mean of economic content per newspaper. The gray shaded area indicates a recession as defined by the NBER. The series have been smoothed with a two-sided rolling window of 4 months for illustrative purposes.

recessions are associated with an increase in the correlation of economic content in newspapers.

As a robustness check, I also estimate (3) using Spearman's rank correlation (see Figure 10). The results are in Column (2) of Table 2.4. Correlation measured by Spearman's rank coefficient also increases during economic expansions. The difference is statistically significant at the 1% level.

The purpose of the previous analysis is to show that recessions are accompanied by an increasing degree of common knowledge about the economic situation. However, if newspapers provide different insights about the economic situation, this would not be the case.

There exist several ways to measure the homogeneity between any two documents. Some of the most common measures used in textual data analysis are cosine similarity and the Jaccard index. Both measures are bounded in $[0, 1]$

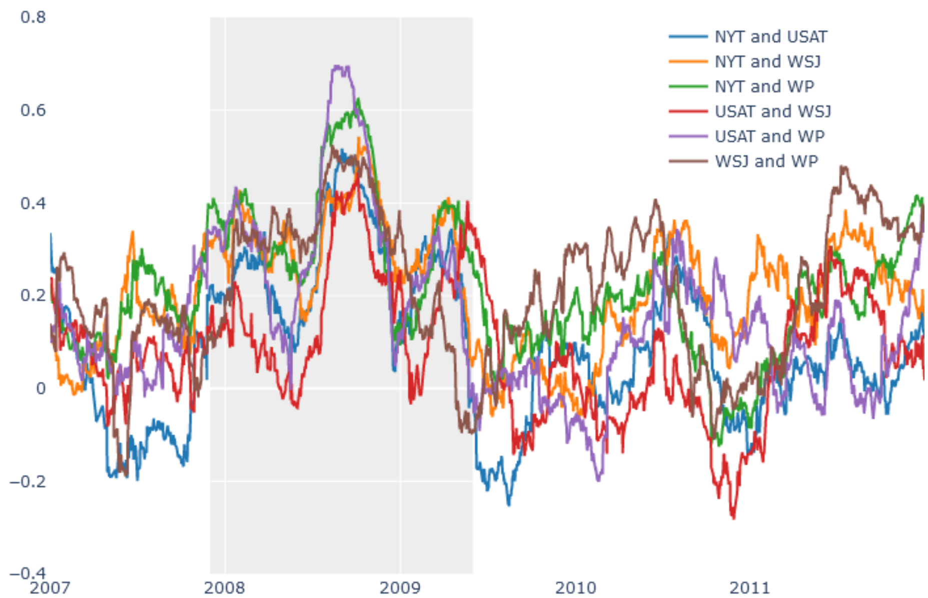

Figure 5: Correlation of the measure of economic content between newspapers. The gray shaded area indicates a recession as defined by the NBER. The series have been smoothed with a two-sided rolling window of 4 months for illustrative purposes.

and thus invariant to the quantity of topics estimated in the LDA, K.

The cosine similarity between two non-zero vectors of dimension n, A and B, is defined as

$$CosineSimil = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

where A_i, B_i are the i-th element of $\mathbf{A}$ and $\mathbf{B}$, respectively. In the context of text analysis, the vectors are topic proportions. In particular, I calculate the similarity between the topic proportions of the front page for each pair of newspapers, and for each day of the sample.

The Jaccard index is defined as the size of the intersection divided by the size of the union of two sets A and B,

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

Table 2: The Impact of Recession on Economic Content

	(1) CorrEconContent	(2) SpearmanRank	(3) CosineSimil	(4) Jaccard
Recession	0.166***	0.0552***	0.0266***	0.00880***
	(0.00263)	(0.0107)	(0.00761)	(0.00137)
_cons	0.104***	0.414***	0.494***	0.787***
	(0.00152)	(0.00616)	(0.00440)	(0.000790)
N	10956	8607	8607	8607
adj. R^2	0.267	0.002	0.001	0.004

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

where $|\cdot|$ is the cardinality of a set. In the context of text analysis, the sets are bags of words. In particular, I calculate the Jaccard index between the sets of words published in the front page for each pair of newspapers, and for each day of the sample.

I then estimate the following model,

$$Simil_{it} = \beta_0 + \beta_1 Recess_t + f_i + u_{it} \tag{4}$$

where $Simil_{it}$ is either cosine similarity or the Jaccard index for a pair of newspapers i in day t. Columns (3) and (4) of Table 2.4 present the results of estimating (4). The point estimates of β_1 for both regressions is greater than zero, and significant at the 1% level. These results speak against the idea that newspapers discuss different topics during regressions, thus bringing further evidence for the case that common knowledge about economic conditions increase during recessions.

To confirm that the results are not driven by the bankruptcy of Lehman Brothers, I repeat the estimation of (3) excluding the observations corresponding to the period between September and November 2008. The results are presented in Table B in Appendix B. Although the estimated increase of correlation is smaller, the results are still statistically significant at the 1% level.

3 The Benchmark Model

In this section, I formalize the mechanism by which mass media can contribute in generating persistent economic downturns. I begin by presenting a stylized model that only features the necessary ingredients. I present the simple version of the model in two steps. First, I develop a dynamic version of the global game with public noise present in Morris and Shin (2000b). It will be useful to highlight the mechanism by which precise public noise can generate persistent falls in economic activity. I then introduce an alternative information structure, to disentangle the role of common knowledge from that of uncertainty.

3.1 The Effect of Public Information

There is a unit mass of risk-neutral agents. Agents in the economy face an infinite-period investment problem. Each of them has an investment opportunity that can either be undertaken or not, $a_i = \{0, 1\}$. The project has an instantaneous payoff,

$$\pi_t = \theta_t + \beta m_t - c$$

where θ_t is the economic fundamental, m_t the mass of agents engaging in the investment opportunity and c the cost of investment. The economy exhibits complementarities if $\beta > 0$.

The fundamental is distributed according to $\theta_t \overset{iid}{\sim} N(\theta_0, \sigma_0)$. The value of θ_t is unknown, but its mean θ_0 is known. In addition, every period agents receive a private signal $x_{it} = \theta_t + \varepsilon_{it}$, and a public signal $z_t = \theta_t + \eta_t$ with $\varepsilon_{it} \sim N(0, \sigma_\varepsilon)$ and $\eta_t \sim N(0, \sigma_\eta)$, respectively. Simple Bayesian updating leads to the following posterior about θ_t,

$$\theta_t | \{x_{it}, z_t\} \sim N\left(\frac{\frac{\theta_0}{\sigma_0^2} + \frac{x_{it}}{\sigma_\varepsilon^2} + \frac{z_t}{\sigma_\eta^2}}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}}, \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2} \right)^{-1} \right) \tag{5}$$

For simplicity, I will denote agent i's expected value of θ_t as $\bar{\theta}_{it}$.

The key difference from Morris and Shin (2000b) is that now investment is persistent: if agents decide to invest, the project will extinguish next period with probability α. Exiting agents are replaced by new ones, and a measure α of the inactive agents receive their own opportunity to invest. Therefore, the mass of investors evolves as follows

$$m_t = (1-\alpha)m_{t-1} + \alpha \int_0^1 a_{it} di \text{ with } \alpha \in [0,1] \tag{6}$$

Persistence is necessary because it will generate non-linearities in the form of multiple steady states. These non-linearities are key to generate persistent downturns.

Solution

Following Morris and Shin (2000b), the equilibrium of this model can be solved by assuming and then verifying a cutoff strategy such that any agent i invests if and only if

$$\bar{\theta}_{it} \geq \kappa_t \tag{7}$$

That is, investment takes place if and only if the expected value of the fundamental, θ_t, exceeds a certain threshold, κ_t. Since the economy is dynamic, the cutoff value is not necessarily constant over time.

Substituting the expected value of the fundamental θ_t into (7), this inequality can also be expressed in terms of the private signal x_{it},

$$x_{it} \geq \sigma_\varepsilon^2 \left(\kappa_t \left(\frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2} \right) - \left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2} \right) \right) \tag{8}$$

For simplicity, agents are myopic. That is, they only focus on the instantaneous payoff of investing when taking their decision, disregarding possible payoffs thereafter. This simplification is done for illustrative purposes. I will restore rational expectations in the quantitative version of the model in Section 4.

To solve for the equilibrium strategy, consider an agent i who believes all other players will follow a cutoff strategy in their investment decision. In any given period t, agent i will invest if and only if their expected payoff is greater than zero. That is, if the following condition holds

$$\begin{aligned}
&\mathbb{E}\left(\theta_t + \beta m_t - c | \{x_{it}, z_t\}\right) \geq 0 \Leftrightarrow \\
&\bar{\theta}_{it} + \beta(1-\alpha)m_{t-1} + \beta\alpha\mathbb{E}\left(\int_0^1 a_{jt}dj \middle| \{x_{it}, z_t\}\right) - c \geq 0
\end{aligned} \tag{9}$$

where the second inequality follows from substituting the expression for the mass of investors (6). The expected mass of new investors is equivalent to the probability any other agent j decides to invest. That is,

$$\mathbb{E}\left(\int_0^1 a_{jt}dj \middle| \{x_{it}, z_t\}\right) = Pr\left(\bar{\theta}_{jt} \geq \kappa_t | \{x_{it}, z_t\}\right)$$

Agent i knows that any other agent's private signal will be equal to θ_t plus a noise term. By standard properties of the normal distribution, the posterior that agent i has about any other agent j's beliefs is the following

$$x_{jt}|\{x_{it}, z_t\} \sim N\left(\bar{\theta}_{it}, \frac{2 + \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}}\right) \tag{10}$$

For simplicity, I will denote the posterior variance of (10) as ζ.

Following the cutoff strategy, agent i beliefs any other agent j will invest if their private signal x_{jt} satisfies the inequality (8). Therefore, the probability agent i assigns to any other agent investing is given by

$$\begin{aligned}
&Pr\left(x_{jt} \geq \sigma_\varepsilon^2\left(\kappa_t\left(\frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right) - \left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2}\right)\right) \middle| \{x_{it}, z_t\}\right) = \\
&\Phi\left(\zeta^{-\frac{1}{2}}\left[\bar{\theta}_{it} + \sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2}\right) - \kappa_t\left(1 + \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)\right)\right]\right)
\end{aligned} \tag{11}$$

where $\Phi(\cdot)$ denotes the CDF of the standard normal distribution. The equality follows from standardizing x_{jt} with its posterior distribution (10).

The equilibrium cutoff is a function $\kappa_t^*(m_{t-1}, z_t)$ implicitly defined by the payoff of the marginal investor. The marginal investor is the agent whose expected value of θ_t is equal to the cutoff κ_t and is therefore indifferent between investing or not. As a results, the equilibrium cutoff is the value that solves

$$\kappa_t^* - c + \beta(1-\alpha)m_{t-1} + \beta\alpha\Phi\left(\zeta^{-\frac{1}{2}}\left[\sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2}\right) - \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)\kappa_t^*\right]\right) = 0 \tag{12}$$

To find the expression for the law of motion of m_t, we still need an expression for the mass of new investors, $\int_0^1 a_{it}di$. The actual mass of new investors is equal to the unconditional probability that an agent's expected value is greater that the cutoff,

$$\begin{aligned} &Pr\left(\bar{\theta}_{it} \geq \kappa_t^*(m_{t-1}, z_t)\right) = \\ &\Phi\left(\frac{1}{\sqrt{\sigma_0^2 + \sigma_\varepsilon^2}}\left[\theta_t + \sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2}\right) - \kappa_t^*(m_{t-1}, z_t)\left(1 + \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)\right)\right]\right) \end{aligned} \tag{13}$$

Therefore, the law of motion of m_t can be expressed as

$$\begin{aligned} m_t = &(1-\alpha)m_{t-1} + \\ &\alpha\Phi\left(\frac{1}{\sqrt{\sigma_0^2 + \sigma_\varepsilon^2}}\left[\theta_t + \sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2} + \frac{z_t}{\sigma_\eta^2}\right) - \kappa_t^*(m_{t-1}, z_t)\left(1 + \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)\right)\right]\right) \end{aligned} \tag{14}$$

The resulting law of motion for m_t is the linear combination of the mass of previous investors m_{t-1} and the S-shaped term, $\Phi(\cdot)$. Therefore, it is possible to have multiple steady states if the second term has a sufficiently high slope. In this setup, transitions between steady states are the key ingredient for public noise to disrupt the economy.[9]

Figure 6 plots the law of motion of m_t in an economy with and without a public signal for different values of the fundamental θ_t.[10] The main feature that stands

[9]The global game setup of the model guarantees uniqueness of equilibrium under well-defined conditions. For a clarification of the distinction between uniqueness of equilibrium and uniqueness of steady sates, see Appendix C.1.

[10]Calibration of the parameters for the benchmark model is available in Appendix C.3.

out is the curvature of the law of motion in the case with public noise. This non-linearity generates multiple steady states for values of the fundamental around its mean, θ_0.

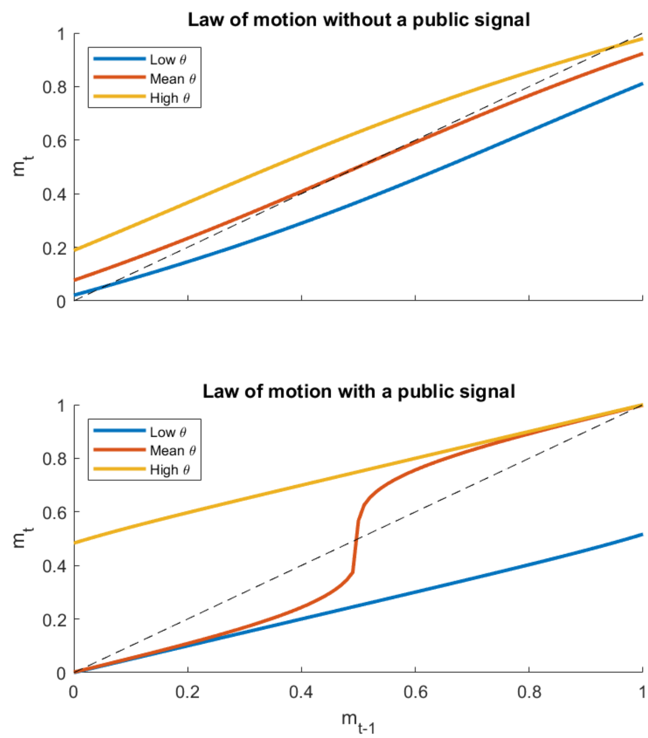

Figure 6: Law of motion of m_t for values of the fundamental, $\theta_t = \{\theta_0 - \sigma_0, \theta_0, \theta_0 + \sigma_0\}$, and for $\eta_t = 0$.

There are two channels that explain this behaviors of the law of motion. First, the equilibrium cutoff (12). The equilibrium cutoff reacts more to the public signal z_t for lower values of the variance of aggregate noise σ_η^2 (see Figure 11). Second, the law of motion (14). The mass of prospect investors is also more responsive to the cutoff for lower values of σ_η^2.

The implications of this effect are important. Consider an economy with $\theta_{t-1} = \theta_0$ that has converged to its steady state. Suppose that the fundamental is slightly perturbed, i.e. $\theta_t = \theta_0 - \varepsilon$ for some ε close to zero. In the absence of a public signal, the economy will converge to a lower steady state. In the event of a recovery, the economy will go back to its previous steady state.

This is not the case with a public signal. Upon arrival of the shock, the economy will first experience a transition to a lower steady state. In addition, the economy will be trapped in a low steady state even if the fundamental goes back to its initial value. It would take a disproportionately positive shock to restore the economy to its initial steady state.

In this setting, public noise makes the economy more susceptible to fall in a low-activity regime. The key to this effect lies in the interaction between the dynamics of investment and the precision of the public signal. A precise public signal coordinates agents' beliefs. Because investment is subject to strategic complementarities, coordinated beliefs translate into coordinated actions. When the fundamental is around its mean, the public signal groups agents' beliefs near the value of the cutoff. Small perturbations to the fundamental drive the decision to invest or not invest of many agents at the same time. If investment is persistent enough, inertia will push the economy to an extreme steady state. The more precise the public signal, the more intense this effect is. In the absence of a public signal, beliefs are dispersed and fewer agents react to small changes in the fundamental.

3.2 A Model with Newspapers

The previous model closely follows the global game with public noise presented in Morris and Shin (2000b). The purpose of that model is to highlight the role of public noise as a coordination device in this economy, and to show how the interaction with the dynamics of investment can generate persistent recessions. However, the presence of a precise public signal confounds the role of public noise as a provider of common knowledge with its associated reduction in uncertainty.

To isolate the role of common knowledge, I rewrite the model with an alternative information structure. In this framework, I show how agents with the same beliefs, facing the same shock and the same uncertainty react differently when there are different levels of common knowledge.

For this purpose, I replace the notion of public signals with newspapers. Newspapers provide noisy information about the state of the fundamental to its readers. Each agent has access to only one newspaper. To keep the analysis tractable, I will consider the case in which there are only two. A fraction $\mu \in (0,1)$ of the population has access to newspaper A, the remaining $(1-\mu)$ only reads newspaper B. Thus, newspapers are semi-public signals with the following structure

$$z_t^n = \theta_t + v_t^n \text{ for } n = \{A, B\} \text{ with } \mathbf{v_t} \sim N\left(\mathbf{0}, \begin{bmatrix} \sigma_\eta^2 & \hbar\sigma_\eta^2 \\ \hbar\sigma_\eta^2 & \sigma_\eta^2 \end{bmatrix}\right) \tag{15}$$

where $\hbar \in [0,1]$ varies the amount of common knowledge present in the economy. One interesting property of this structure is that agents face the same amount of uncertainty whatever the value of $\hbar$ is. A higher $\hbar$ provides more information about what the readers of the other newspaper know, but it gives no additional information about the value of fundamental.

Solution

Overall, the model is solved in following the same procedure as in Section 3.1. However, an important aspect changes with respect to the benchmark model. Since the population is partitioned, each fraction of the population will have their own cutoff.

Assume WLOG that agent i is a newspaper A reader. Following the cutoff strategy (7), agent i will decide to invest if and only if

$$\bar{\theta}_{it}^A + \beta(1-\alpha)m_{t-1} + \beta\alpha\mathbb{E}\left(\int_0^1 a_{jt}dj \middle| \{x_{it}, z_t^A\}\right) - c \geq 0$$

where $\bar{\theta}_{it}^A$ is the expected value of the fundamental conditional on $\{x_{it}, z_t^A\}$. The expected mass of new investors is now given by

$$\mathbb{E}\left(\int_0^1 a_{jt}dj\Big|\{x_{it},z_t^A\}\right)=\mu Pr\left(\bar{\theta}_{jt}^A\geq\kappa_t^A|\{x_{it},z_t^A\}\right)$$
$$+(1-\mu)Pr\left(\bar{\theta}_{jt}^B\geq\kappa_t^B|\{x_{it},z_t^A\}\right) \tag{16}$$

Agent i's problem when calculating the first term of (16) is exactly the same as in the previous section. The reason is that newspaper A readers share common information, z_t^A. This is not the case with the second term of (16). To see why, notice that

$$Pr\left(\bar{\theta}_{jt}^B\geq\kappa_t^B|\{x_{it},z_t^A\}\right)=Pr\left(\frac{\frac{\theta_0}{\sigma_0^2}+\frac{x_{it}}{\sigma_\varepsilon^2}+\frac{z_t^B}{\sigma_\eta^2}}{\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}}\geq\kappa_t^B|\{x_{it},z_t^A\}\right)$$

where z_t^B is unobserved by a newspaper A reader. Thus, agent i expects newspaper B readers to invest if their signals satisfy

$$\frac{x_{jt}}{\sigma_\varepsilon^2}+\frac{z_t^B}{\sigma_\eta^2}\geq\kappa_t^B\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)-\frac{\theta_0}{\sigma_0^2}$$

To newspaper A readers, z_t^B is unobserved and thus a second unknown. However, even if newspaper A readers cannot observe the value z_t^B, they can still learn from it through their own newspaper as long as the correlation of noise $\hbar\neq 0$. This correlated information between the partitioned population will (act as an amplification mechanism).

Any newspaper A reader has the following posterior over newspaper B

$$z_t^B|\{x_{it},z_t^A\}\sim N\left(\psi_0\theta_0+\psi_x x_{it}+\psi_z z_t^A,(1-\hbar)\sigma_\eta^2\left(1+\frac{\frac{1}{\sigma_\eta^2}+\hbar\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}\right)}{\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}}\right)\right)$$

where ψ_0,ψ_x,ψ_z are the weights agents give to the prior, their private signal and their newspaper, respectively[11]

$$\psi_0 \equiv \left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)^{-1}\left(\frac{1-\hbar}{\sigma_0^2}\right)$$
$$\psi_x \equiv \left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)^{-1}\left(\frac{1-\hbar}{\sigma_\varepsilon^2}\right)$$
$$\psi_z \equiv \left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)^{-1}\left(\frac{1}{\sigma_\eta^2}+\hbar\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}\right)\right)$$

Naturally, the higher the degree of common knowledge $\hbar$, the more relative weight attributed to z_t^A. Similarly, the higher the degree of common knowledge $\hbar$, the less uncertainty regarding the other population's information.

Consequently, the probability agent i assigns to any newspaper B reader investing is given by

$$Pr\left(\frac{x_{jt}}{\sigma_\varepsilon^2}+\frac{z_t^B}{\sigma_\eta^2}\geq \kappa_t^B\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)-\frac{\theta_0}{\sigma_0^2}\middle|\{x_{it},z_t^A\}\right)=$$
$$\Phi\left(\zeta_2^{-\frac{1}{2}}\left[\frac{\theta_0}{\sigma_0^2}+\bar{\theta}_{it}\left(\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)+\frac{\frac{\hbar}{\sigma_\eta^2}\left(z_t^A\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}\right)-\frac{x_{it}}{\sigma_\varepsilon^2}-\frac{\theta_0}{\sigma_0^2}\right)}{\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}}-\kappa_t^B\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)\right]\right)$$

where the equality follows from standardizing the variable

$$\frac{x_{jt}}{\sigma_\varepsilon^2}+\frac{z_t^B}{\sigma_\eta^2}\middle|\{x_{it},z_t^A\}$$

with its posterior distribution.[12]

Finally, as in the the case without newspapers, the cutoff for a newspaper A reader is implicitly defined by the marginal investor

$$\kappa_t^{A*}+\beta(1-\alpha)m_{t-1}-c+\beta\alpha\mu\Phi\left(\zeta^{-\frac{1}{2}}\left[\sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2}+\frac{z_t^A}{\sigma_\eta^2}\right)-\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\eta^2}\right)\kappa_t^{A*}\right]\right) \tag{17}$$
$$+\beta\alpha(1-\mu)\Phi\left(\zeta_2^{-\frac{1}{2}}\left[\frac{\theta_0}{\sigma_0^2}+\kappa_t^{A*}\left(\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)-\kappa_t^{B*}\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}\right)+\hbar\frac{\left(z_t^A-\kappa_t^{A*}\right)}{\sigma_\eta^2}\right]\right)=0$$

Together with the analogue expression for a Newspaper B reader, this condition gives rise to the equilibrium cutoffs $\kappa_t^{A*}(m_{t-1},z_t^A,\kappa_t^{B*})$ and $\kappa_t^{B*}(m_{t-1},z_t^B,\kappa_t^{A*})$.

[11] See Appendix C.2 for the full derivation.

[12] See Appendix C.2 for more details.

Notice that when $\hbar > 0$, newspaper A readers use their own cutoff to estimate the proportion of newspaper B readers that are going to invest.

The resulting law of motion is the weighted average of the mass of new investors in every population

$$\begin{aligned} m_t &= (1-\alpha)m_{t-1} \qquad (18) \\ &+ \alpha\mu\Phi\left(\frac{1}{\sqrt{\sigma_0^2+\sigma_\varepsilon^2}}\left[\theta_t + \sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2}+\frac{z_t^A}{\sigma_\eta^2}\right) - \kappa_t^{A*}(m_{t-1}, z_t^A, \kappa_t^{B*})\left(1+\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\eta^2}\right)\right)\right]\right) \\ &+ \alpha(1-\mu)\Phi\left(\frac{1}{\sqrt{\sigma_0^2+\sigma_\varepsilon^2}}\left[\theta_t + \sigma_\varepsilon^2\left(\frac{\theta_0}{\sigma_0^2}+\frac{z_t^B}{\sigma_\eta^2}\right) - \kappa_t^{B*}(m_{t-1}, z_t^B, \kappa_t^{A*})\left(1+\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{1}{\sigma_\eta^2}\right)\right)\right]\right) \end{aligned}$$

Figure 7 plots the law of motion of m_t in an economy for different values of the the correlation of noise $\hbar$. An increase in $\hbar$ has the same effect as a decrease in the variance of aggregate noise, σ_η^2. The effect, however, is less marked because in this case only one channel is operating. In the previous case, a decrease in σ_η^2 operates through the equilibrium cutoff (12) and through the mass of new investors (14). In this case, variations in $\hbar$ have an effect only through the equilibrium cutoff, (17).

4 Quantitative Model

To evaluate empirically the importance of variations in common knowledge, I embed the mechanism into a general equilibrium model. For this purpose, I add the information structure of the previous section to the business cycle model in Schaal and Taschereau-Dumouchel (2015). In addition, this model allows me to restore rational expectations.

The model features the same key elements as the one in Section 3. Agents imperfectly observe the fundamental through a signal structure (15) and face a binary decision – capacity utilization, in this case. Persistence is ensured by the presence of capital.

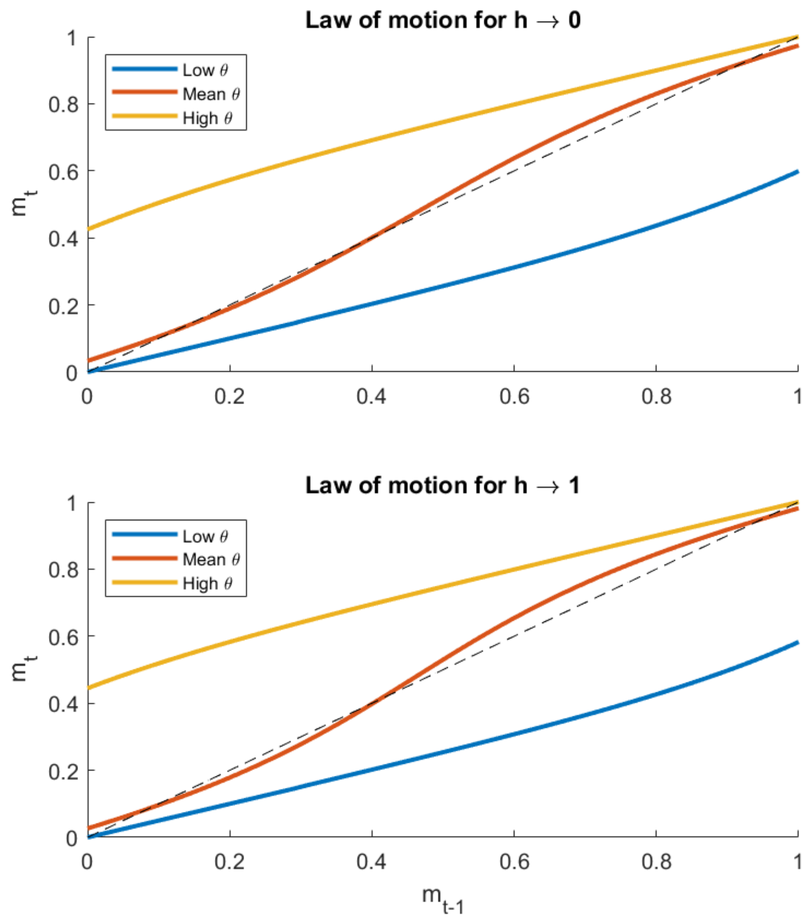

Figure 7: Law of motion of m_t for values of the fundamental, $\theta_t = \{\theta_0 - \sigma_0, \theta_0, \theta_0 + \sigma_0\}$, and for $\eta_t = 0$.

4.1 Environment

Time is discrete and goes on forever. The economy consists of a representative household, a final good sector and an intermediate good sector. The final good is produced by a representative firm, and can be used both for consumption and investment. The intermediate goods are produced by a continuum of monopolists, and are solely used to produce the final good.

Households and Preferences

The representative household maximizes lifetime utility

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t U(C_t, L_t) \tag{19}$$

where $\beta \in (0,1)$ is the discount factor, $C_t \geq 0$ is the amount of the final good consumed and $L_t \geq 0$ is labor. The period utility of the household is given by GHH preferences (Greenwood et al., 1988)

$$U(C_t, L_t) = \frac{1}{1-\gamma}\left(C_t - \left(\frac{L_t^{1+\nu}}{1+\nu}\right)^{1-\gamma}\right) \text{ with } \gamma > 0, \nu > 0 \tag{20}$$

The representative household owns the final good and the intermediate good firms. It also supplies capital K_t and labor L_t in perfectly competitive markets. Every period, the representative household faces the following budget constraint

$$P_t\left(C_t + K_{t+1} - (1-\delta)K_t\right) \leq W_t L_t + R_t K_t + \Pi_t \tag{21}$$

where P_t is the price of the final good, W_t the wage rate, R_t the rental rate of capital and Π_t the profits from the firms. Capital depreciates at rate $0 < \delta < 1$.

Final Good Producer

The final good is produced by a representative firm in a perfectly competitive market. The final good producer aggregates the output of the intermediate sector monopolists using a Dixit-Stiglitz (1980) aggregator

$$Y_t = \left(\int_0^1 Y_{it}^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \tag{22}$$

where $\sigma > 1$ is the elasticity of substitution between varieties, Y_t is the amount of the final good produced and Y_{it} is the input of intermediate good i. Profit maximization, taking prices as given, results in the following demand curve for every intermediate good i,

$$Y_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\sigma} \text{ with } P_t = \left(\int_0^1 P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{23}$$

Intermediate Good Producers

Intermediate goods producers have access to the following constant returns to scale production technology

$$Y_{it} = Ae^{\theta_t} u_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \tag{24}$$

where $\alpha \in (0, 1)$ is the capital share, K_{it} and L_{it} are capital and labor, and u_{it} is capacity utilization. Productivity depends on a constant scaling factor A and on a fundamental θ_t which follows an AR(1) process,

$$\theta_t = \rho\theta_{t-1} + \xi_t \tag{25}$$

where $\xi_t \sim N(0, \sigma_\xi)$.

Capacity utilization can either be low, $u_l = 1$, or high, $u_h = \omega > 1$. Production at high capacity requires a fixed cost $c > 0$. For a given choice of capacity utilization, intermediate producers solve the following production problem:

$$\Pi_{it} = \max_{Y_{it}, P_{it}, K_{it}, L_{it}} P_{it}Y_{it} - R_t K_{it} - W_t L_{it} \tag{26}$$

subject to the demand curve (23) and to the production technology (24). Intermediate producers take the rental rate of capital R_t and the wage W_t as given.

Information and Timing

Each period t is divided in two stages. In the first stage, intermediate producers choose their capacity decision u_{it} under incomplete information about the fundamental θ_t. As in the baseline model, firms imperfectly observe the fundamental θ_t through a private signal x_{it} and a newspaper z_t^n for $n = \{A, B\}$. In addition, agents know all past realizations of the fundamental. Since productivity shocks follow an AR(1) process, the ex-ante beliefs about current productivity are given by $\theta_t|\theta_{t-1} \sim N(\rho\theta_{t-1}, \sigma_0)$. After observing the private signal and the newspapers, firms update their beliefs as follows

$$\theta_t|\{\theta_{t-1}, x_{it}, z_t^n\} \sim N\left(\frac{\frac{\theta_{t-1}}{\sigma_0^2} + \frac{x_{it}}{\sigma_\varepsilon^2} + \frac{z_t^n}{\sigma_\eta^2}}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}}, \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}\right)^{-1}\right) \tag{27}$$

In the second stage, the value of the fundamental is revealed. Households make consumption-savings decisions, firms make production decisions and markets clear.

Characterization

I will briefly characterize some of the results of the model.[13] There are two aspects that simplify the solution of this model. First, because of the GHH preferences, the household's labor and consumption-savings decisions are independent. Thus the household's problem is still characterized by the standard conditions:

$$U_C(C_t, L_t) = \beta \mathbb{E}\left[(R_{t+1} + 1 - \delta) U_C(C_{t+1}, L_{t+1})\right] \text{ and } L_t^{\nu} = \frac{W_t}{P_t} \tag{28}$$

In addition, because the fundamental is revealed in the second stage of the problem, production decisions can be solved by the standard first-order conditions, taking the level of capacity decision as given. The optimal level capacity utilization for every firm is given by

$$u_{it} = \begin{cases} u_h \text{ if } \Delta\Pi(K_t, \theta_{t-1}, m_t, z_t^n, x_{it}) > 0 \\ u_l \text{ if } \Delta\Pi(K_t, \theta_{t-1}, m_t, z_t^n, x_{it}) \leq 0 \end{cases} \tag{29}$$

where $\Delta\Pi(K_t, \theta_{t-1}, m_t, z_t^n, x_{it}) \equiv \mathbb{E}\left[\Pi_{ht}(K_t, \theta_t, m_t) - c - \Pi_{lt}(K_t, \theta_t, m_t) | \theta_{t-1}, z_t^n, x_{it}\right]$ is the expected surplus of choosing a high capacity utilization.

Under imperfect information, the mass of firms operating at high capacity, m_t, will be pinned down endogenously. Because the economy is populated by heterogeneous firms producing at possibly different capacities, the production of the final good will be as follows

$$\begin{aligned} Y_t &= \left(m_t Y_{ht}^{\frac{\sigma-1}{\sigma}} + (1 - m_t) Y_{lt}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \\ &= \bar{A}(\theta_t, m_t) K_t^{\alpha} L_t^{(1-\alpha)} \end{aligned} \tag{30}$$

[13] See (Schaal and Taschereau-Dumouchel, 2015) for more details.

where $\bar{A}(\theta_t, m_t) \equiv \left(m_t(A\omega e^{\theta_t})^{\sigma-1} + (1-m_t)(Ae^{\theta_t})^{\frac{\sigma-1}{\sigma}}\right)^{\sigma-1}$. That is, in equilibrium the economy behaves as if it were populated by a representative firm with an endogenous TFP, $\bar{A}$.

4.2 Evaluation

To assess the quantitative relevance of the model, I simulate the economy for 30000 periods. The calibration of the model can be found in Table 8. The calibration of the model resembles that of Schaal and Taschereau-Dumouchel (2015), except the correlation of newspapers, $\hbar$. I calibrate $\hbar$ using the results from Section 2. In particular, recall that the correlation of economic content in US newspapers averages 0.1 during periods of growth, and 0.26 during recessions. In that spirit, I calibrate the correlation of newspapers as $\hbar = 0.10$ when the economy is in a high activity regime (i.e. $m_t = 1$), and $\hbar = 0.26$ when the economy is in a low activity regime (i.e. $m_t = 0$).

Figure 8 presents the results of the simulation. Despite the normality of the fundamental, aggregate variables present bimodal distributions and are skewed to the left. In order to offer a comparison with the data from the US economy, I present the simulated data as log deviations from the steady state with high capacity utilization.

Figure 9 presents the histograms of the same aggregate variables for the US economy for the 1985 - 2015 period. The model is able to replicate the bimodality and the skewness of the main aggregate variables, two key features of the data that a standard RBC model cannot. Investment, however, appears to be more disperse than the model can capture. For comparison with the simulated data, I remove a linear trend form the log time series.

5 Conclusion

In this paper, I document that mass media become more coordinated when the economy is in a recession. This new stylized fact about economic reporting

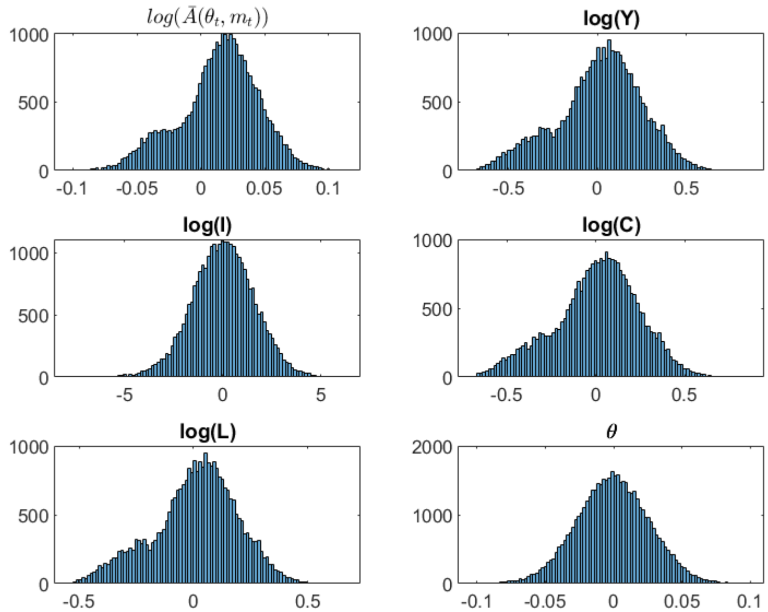

Figure 8: Histogram of simulated data.

highlights the importance of fluctuations in imperfect common knowledge for the business cycle. Motivated by this evidence, I present a framework to explain the contribution of mass media in generating persistent economic downturns.

In this setup, as mass media become more coordinated, economic conditions become more common knowledge among firms. During a recession, the decision of firms not to invest is amplified because they are aware that other firms are also not willing to invest. Mass media then contribute to the business cycle by increasing awareness of the economic conditions. This increase in common knowledge can turn an otherwise mild recession into a persistent slump.

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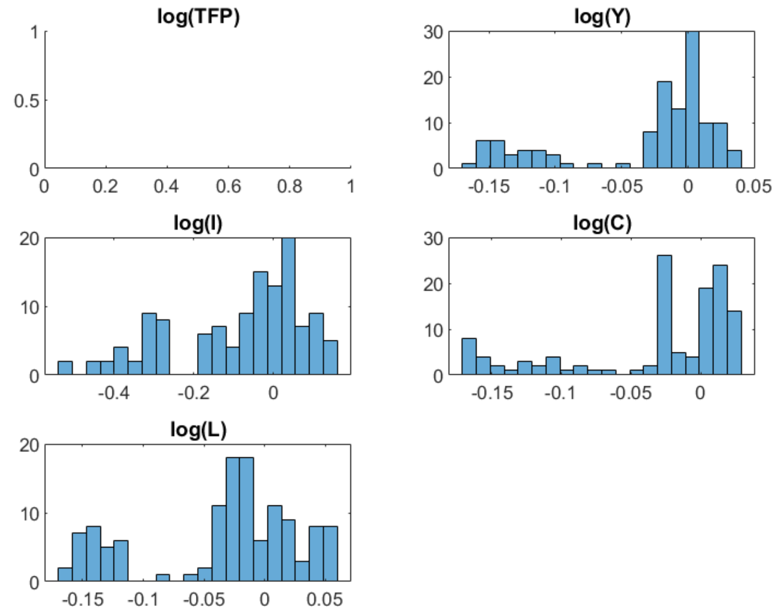

Figure 9: Histogram of US aggregate data.

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A Technical Details of the LDA

A.1 Preprocessing Text

A proper cleaning of the textual data is key to obtain easy-to-interpret results. Although idiosyncrasies present in every set of documents make the preprocessing of texts almost a matter of craftsmanship, several procedures are common when working with LDA.

The first step is removing *stop words* and punctuation. Stop words refer to terms that are widely used in a language (e.g. "the", "is", "at"). These terms usually provide no substantive meaning and hinder the interpretation of topics. There exists no unique list of stop words. I use the stop word list provided in Python's Natural Language ToolKit package developed by Bird (2002). Punctuation need also be removed, as it provides no meaning in the context of LDA.

The second step is *lemmatization*. Lemmatization is the act of grouping together the inflected forms of a word for analysis as a single item (Collins, 2020). In many languages, words are inflected. In the context of LDA, inflection can be problematic. For example, LDA considers the words "walk" and "walks" as different, even though they share the same lemma and convey the same meaning. Lemmatization is thus a procedure used to avoid losses in LDA due to the breaking up of a same lemma into different terms. I use lemmatization algorithm provided in Python's spaCy package developed by Honnibal and Montani (2017).

The last step is *trimming*. In the context of reporting, there are several words relative to time (e.g. "today", "week") and verbs (e.g. "say", "take", "make") that convey no meaning but are not included in the stop word list. I thus trim words appearing in either more than half or less than 5 of the articles.

A.2 Specification of the LDA and the Choice of K

As mentioned in Section 2.2, I apply the Gibbs sampling algorithm developed by McCallum (2002). Originally programmed in Java, the gensim package provides

K	Coherence
20.0	0.640
30.0	0.658
40.0	0.671
50.0	0.662

Table 3: Coherence of the LDA model for different choices of the number of topics K.

a wrapper that allows to use this algorithm in Python (Rehurek and Sojka, 2010). The key choice when using LDA models is the number of topics K. Given the unsupervised nature of the model, there is no *correct* choice of K. However, there exist semantic measures of coherence that can be used to measure the meaningfulness of topics (Chang et al., 2009).

The gensim package includes a routine to calculate the coherence of a model given K. I thus run the LDA for $K = \{20, 30, 40, 50\}$. Table 3 shows the coherence for each K. The highest value of coherence corresponds with $K = 40$.

A.3 Results from LDA

Tables 4 and 5 present the topics estimated by the LDA, together with its label.

Topic ID	**Label**	**Top Words**
0	Retail	store retailer sale consumer shopper buy shopping holiday mart wal chain
1	Firm Management	company big firm executive business bank deal group investor financial sell
2	Russia	russia russian moscow putin vladimir soviet georgia venezuela kremlin chavez
3	Local	county yesterday virginia prince maryland district george area school fairfax
4	Shooting	shoot kill shooting police virginia wound tech student hood gunman fort
5	*Stocks*	*market price stock economy world global fall investor industrial rise point*
6	Traffic	car driver road traffic vehicle drive highway gas transportation mile metro
7	-	page article correction incorrectly publish amplification front space mine
8	BP	oil gulf mexico spill company coast drilling rig offshore gas water disaster
9	Natural Disasters	hurricane storm earthquake people katrina coast haiti water city port prince
10	Obamacare	health care obama insurance system bill overhaul coverage plan debate
11	Automotive	auto general company car detroit motors industry chrysler bankruptcy
12	Judicial	court supreme justice law rule decision judge case federal state ruling
13	Arab Spring	libya force government protest egypt protester cairo power leader military
14	Federal	official department bush accord yesterday agency federal report investigation
15	Terrorism	pakistan qaeda attack official pakistani kill intelligence american militant
16	*Mortgage*	*mortgage home housing loan foreclosure market credit estate real lender*
17	Health	drug health medical doctor patient study disease find hospital cancer
18	Campaing	barack presidential clinton john hillary democratic obama campaign senator
19	Food	food grow farm eat farmer china crop restaurant corn product chinese field

Table 4: Estimated LDA topics (0 - 19): label and high-probability words. In italics, economics-related topics.

Topic ID	**Label**	**Top Words**
20	Immigration	immigrant illegal mexico immigration drug border mexican law country
21	GOP	republican election party candidate voter campaign presidential race political
22	Middle East	israel israeli palestinian gaza middle minister hamas saudi arab prime
23	States	gov governor state albany sarah palin mayor tuesday alaska city andrew
24	Entertainment	show game los star angeles team play good season big sunday fan
25	*Trials*	*case charge federal court prison prosecutor crime suspect trial criminal*
26	Technology	company internet web online computer site technology google phone
27	*Stimulus*	*financial bank federal crisis government reserve treasury rescue market bailout*
28	Air Travel	flight air airport plane airline passenger security fly jet travel safety airlines
29	*Economic Outlook*	*job economy show accord rate nation high number report rise find americans*
30	War	afghanistan military troop war afghan taliban force army iraq commander
31	*European Debt*	*european europe debt crisis euro greece financial union minister london*
32	Diplomacy	obama official administration government country united states begin nation
33	Pensions	government state pay money cut federal tax budget plan program dollar cost
34	Iraq	iraq baghdad iraqi troop american bush military war shiite security force iraqis
35	Environment	plant climate power gas japan energy global nuclear environmental warming
36	Legislative	house senate democrats republican leader congress republicans vote bill
37	Profiles	home man family city long leave work call find house run hour begin
38	Education	school student high university college teacher education church class
39	Nuclear	iran nuclear iranian weapon tehran korea north program country sanction korean

Table 5: Estimated LDA topics (20 - 39): label and high-probability words. In italics, economics-related topics.

Text Snippet	**Publication**	**2^{nd} Topic**	**T12**	**T28**	**T40**	**T42**	**T43**	**T48**
Barclays in Sanctions Bust – U.K. Firm to Pay $298 Million to Settle Charges Involving Iran. Barclays PLC agreed to pay 298 million to settle charges by U.S. and New York prosecutors that the U.K. bank altered financial records for more than a decade...	Firm Mgmt T1: 0.47	Federal T14: 0.21	0.000	0.039	0.000	0.000	0.001	0.000
Denmark's 'flexicurity' blends welfare state, economic growth. Across Europe, nations such as France, Italy and Germany struggle with lackluster economic growth, high unemployment and high taxes...	European Debt T31: 0.48	Economic Outlook T29: 0.20	0.487	0.000	0.001	0.124	0.001	0.205
Iraq's turbulent effort to reckon with the violence of its past took another macabre turn on Monday when the execution of Saddam Hussein's half brother ended with...	Profiles T37: 0.43	Middle East T22: 0.30	0.000	0.000	0.000	0.000	0.000	0.000
Job Losses Worst Since '74: 533,000 Shed in November. The U.S. lost half a million jobs in November, the largest one-month drop since 1974, as employers brace for a recession...	Economic Outlook T29: 0.86	-	0.000	0.000	0.001	0.001	0.001	0.864

B Robustness of the Results

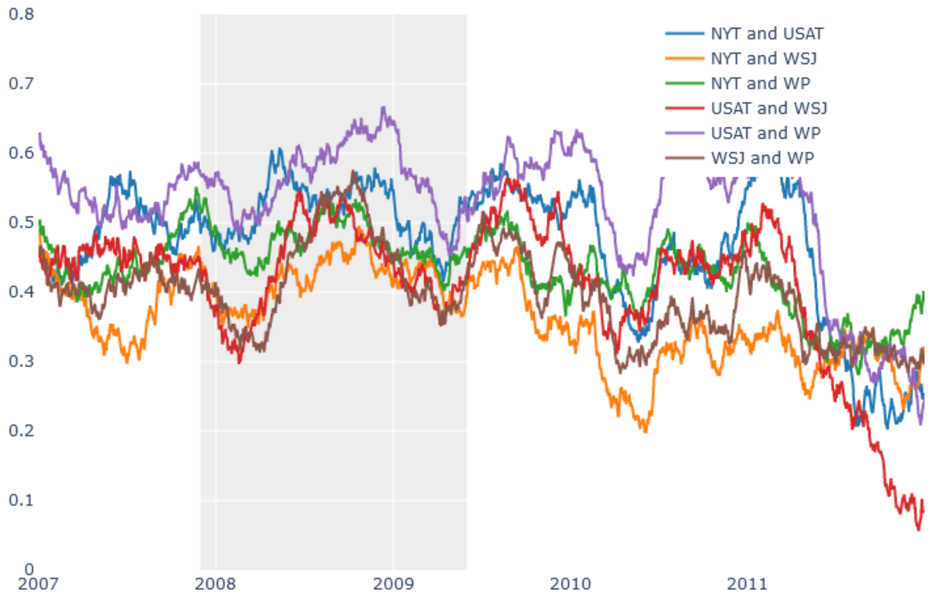

Figure 10: Spearman's rank correlation of the measure of economic content between newspapers. The gray shaded area indicates a recession as defined by the NBER. The series have been smoothed with a two-sided rolling window of 4 months for illustrative purposes.

Table 6: The Impact of Recession on Economic Content

	(1)	(2)	(3)	(4)
	CorrEconContent	SpearmanRank	CosineSimil	Jaccard
Recession	0.135^{***}	0.0372^{**}	0.00588	0.00748^{***}
	(0.00264)	(0.0113)	(0.00800)	(0.00145)
_cons	0.104^{***}	0.414^{***}	0.494^{***}	0.787^{***}
	(0.00144)	(0.00620)	(0.00437)	(0.000795)
N	10422	8180	8180	8180
adj. R^2	0.199	0.001	-0.001	0.002

Standard errors in parentheses.

These results exclude the obsevations between September and November 2008.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Appendix: Section 3

C.1 Decoupling equilibrium and steady state

One interesting feature of this framework is that allows to make a clear distinction between multiplicity of equilibria and of steady states, thus highlighting the different forces behind both phenomena.

PROPOSITION 1: *A sufficient condition that guarantees uniqueness of the equilibrium cutoff is given by*

$$\left(\frac{2+\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right)}{\frac{1}{\sigma^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}}\right)^{-\frac{1}{2}}\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right) > \frac{\alpha\beta}{\sqrt{2\pi}} \tag{31}$$

where

$$\tau_E \equiv \left(\frac{2+\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right)}{\frac{1}{\sigma^2}+\frac{1}{\sigma_\varepsilon^2}+\frac{1}{\sigma_\eta^2}}\right)^{-\frac{1}{2}}\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right) \tag{32}$$

is the expected response of investment to a marginal increase in κ_t^*.[14]

[14]This expression results from taking the derivative of an agent's *expected* – conditional on

PROOF:

Follows from Appendix A in Morris and Shin (2000a). □

The interpretation of the equilibrium uniqueness condition in this setup is very similar to previous results form the global games literature[15]. The equilibrium will be unique if *contemporaneous* complementarities ($\alpha\beta$) are weak; or if the *expected* response of investment to a marginal increase in the equilibrium cutoff (32) is strong. Alternatively, the second condition can also be interpreted as the requirement that private information be precise relative to public.

COROLLARY 1: *If agents' actions exhibit complementarities ($\beta > 0$), and condition (31) is satisfied, then the equilibrium cutoff at time t is decreasing in the previous mass of investors, m_{t-1}.*

PROOF:

By implicitly differentiating the payoff function (9), a sufficient condition for the cutoff to be decreasing in m_{t-1} if

$$\frac{\partial \kappa_t^*}{\partial m_{t-1}} = -\frac{\beta(1-\alpha)}{\left[1-\sqrt{2\pi}\alpha\beta\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right)\gamma^{-\frac{1}{2}}\right]} \leq 0$$

which is negative if $\beta < 0$ and (31) is satisfied. □

PROPOSITION 2: *If the inequality*

$$(1-\alpha)\beta\left(\frac{1+\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right)}{\sqrt{\sigma^2+\sigma_\varepsilon^2}}\right) > \left(\sqrt{2\pi}-\alpha\beta\xi^E\right) \tag{33}$$

holds, where

$$\tau_A \equiv \frac{1+\sigma_\varepsilon^2\left(\frac{1}{\sigma^2}+\frac{1}{\sigma_\eta^2}\right)}{\sqrt{\sigma^2+\sigma_\varepsilon^2}} \tag{34}$$

---

her information – proportion of new investors, $Pr\left(\bar{\theta}_{jt} \geq \kappa_t^* | \mathcal{I}_{it}\right)$, with respect to the equilibrium cutoff κ_t^*.

[15]In fact, when the public signal is diffuse, i.e. $\sigma_\eta^2 \to \infty$, this condition converges to Proposition 3.1 in Morris and Shin (2000b).

is the actual response of investment to a marginal increase in κ_t^**; then there exists (at least one) value of the fundamental for which the economy exhibits multiple steady states.*[16]

PROOF: (TBF) □

Condition (33) essentially states that to have multiple steady states either *past* complementarities ($(1-\alpha)\beta$) are strong; or the *actual* response of investment to a marginal increase in the equilibrium cutoff (34) is weak.

The two propositions provide analogue conditions related to the strength of complementarities and the response of investment. However, there are some subtle differences between both of them worth discussing. In general, strong complementarities generate multiple equilibria and, inevitably, multiple steady states. The contrary is not true. Multiple steady states can be present in a model with a unique equilibrium (e.g. Fajgelbaum, Schaal and Taschereau-Dumouchel, 2017).

The results from Propositions 1 and 2 highlight that the roots of both phenomena are not the same. Multiplicity of equilibria has a forward-looking origin – contemporaneous in this setup, because of the myopic agents assumption –, linked to the decisions of prospect investors. On the other hand, multiplicity of steady states is a backward-looking phenomenon, related to the decision of previous investors.

To sustain a unique equilibrium, complementarities in the investment decisions by new investors should not be too strong, whereas expectations have to react strongly to changes in the cutoff. Otherwise, fundamental values by themselves will not be enough to pin down the equilibrium. To sustain multiple steady states, past investment decisions have to exert a strong complementarity on current ones. There is thus a trade off between past and contemporaneous complementarities. In addition, the response of investment to changes in the

[16] This expression results from taking the derivative of an the *actual* proportion of investors, $Pr\left(\bar{\theta}_{jt} \geq \kappa_t^*\right)$, with respect to the cutoff κ_t^*.

cutoff has to be weak to ensure the existence of transition dynamics between steady states, and not simply jumps from one to another.

The precision of public noise has an effect on the reaction of investment (expected or actual) to a change in the cutoff, but not on complementarities. In particular, the more precise the public signal, the stronger the reaction of (expected or actual) investment

$$\frac{\partial \tau^E}{\partial \sigma_\eta^2} < 0 \text{ and } \frac{\partial \tau^A}{\partial \sigma_\eta^2} < 0$$

That is, a more precise public signal relaxes the conditions to obtain steady state. However, too much precision can eventually restore equilibrium multiplicity. This means that the transition between uniqueness and indeterminacy regions is not direct. Instead, there is now an intermediate region characterized by a unique equilibrium but multiple steady states.

C.2 Newspaper A reader's posterior of Newspaper B

The private signals and the two newspapers are three random variables distributed as follows

$$\begin{bmatrix} x_{it} \\ z_t^A \\ z_t^B \end{bmatrix} \sim N\left(\theta_{\mathbf{0}}, \begin{bmatrix} \sigma_0^2 + \sigma_\varepsilon^2 & \sigma_0^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + \sigma_\eta^2 & \sigma_0^2 + \hbar\sigma_\eta^2 \\ \sigma_0^2 & \sigma_0^2 + \hbar\sigma_\eta^2 & \sigma_0^2 + \sigma_\eta^2 \end{bmatrix}\right)$$

The problem for any newspaper A reader is to find the posterior of z_t^B with their own information $\{x_{it}, z_t^A\}$. By standard properties of the normal distribution,

$$\begin{aligned}
&\mathbb{E}(z_t^B | x_{it}, z_t^A) = \\
&= \theta_0 + \begin{bmatrix} \sigma_0^2 & \sigma_0^2 + \hbar\sigma_\eta^2 \end{bmatrix} \begin{bmatrix} \sigma_0^2 + \sigma_\varepsilon^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + \sigma_\eta^2 \end{bmatrix}^{-1} \begin{bmatrix} x_{it} - \theta_0 \\ z_t^A - \theta_0 \end{bmatrix} \\
&= \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}\right)^{-1} \left[\theta_0 \left(\frac{1-\hbar}{\sigma_0^2}\right) + x_{it}\left(\frac{1-\hbar}{\sigma_\varepsilon^2}\right) + z_t^A \left(\frac{1}{\sigma_\eta^2} + \hbar\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2}\right)\right)\right]
\end{aligned}$$

and

$$
\begin{aligned}
&\mathbb{V}(z_t^B|x_{it}, z_t^A) = \\
&\quad = \sigma_0^2 + \sigma_\eta^2 - \begin{bmatrix} \sigma_0^2 & \sigma_0^2 + \hbar\sigma_\eta^2 \end{bmatrix} \begin{bmatrix} \sigma_0^2 + \sigma_\varepsilon^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + \sigma_\eta^2 \end{bmatrix}^{-1} \begin{bmatrix} \sigma_0^2 \\ \sigma_0^2 + \hbar\sigma_\eta^2 \end{bmatrix} \\
&\quad = (1-\hbar)\sigma_\eta^2 \left(1 + \frac{\frac{1}{\sigma_\eta^2} + \hbar\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2}\right)}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}} \right)
\end{aligned}
$$

Then, the random variable

$$
\frac{x_{jt}}{\sigma_\varepsilon^2} + \frac{z_t^B}{\sigma_\eta^2} \Big| \{x_{it}, z_t^A\}
$$

has the following mean

$$
\begin{aligned}
\bar{\mu}(x_{it}, z_t^A) \equiv \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}\right)^{-1} \Bigg[& \frac{\theta_0}{\sigma_0^2}\left(\frac{1}{\sigma_\varepsilon^2} + \frac{1-\hbar}{\sigma_\eta^2}\right) \\
& + \frac{x_{it}}{\sigma_\varepsilon^2}\left(\frac{1}{\sigma_\varepsilon^2} + \frac{1-\hbar}{\sigma_\eta^2}\right) \\
& + \frac{z_t^A}{\sigma_\eta^2}\left(\frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2} + \hbar\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2}\right)\right)\Bigg]
\end{aligned}
$$

and the following variance

$$
\begin{aligned}
\zeta_2 \equiv \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\eta^2}\right)^{-1} \Bigg[& \frac{1}{\sigma_\varepsilon^4}\left(2 + \sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\eta^2}\right)\right) \\
& + \frac{1}{\sigma_\eta^4}(1-\hbar)\left(\frac{2}{\sigma_\eta^2} + \sigma_\eta^2(1+\hbar)\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2}\right)\right)\Bigg] + \frac{2\sigma_0^2}{\sigma_\varepsilon^2\sigma_\eta^2}
\end{aligned}
$$

C.3 Calibration

Table 7 shows the calibrated parameters for the benchmark model. I set the scaling factor β such that there are multiple equilibria in the presence of perfect information. I set the rest of the parameters such that the economy has a unique steady state when there is no public signal, but it has a unique equilibrium with multiple steady states when the signal is more precise.

Investment		
α	Persistence probability	0.5
β	Complementarity	3
c	Cost	2
Fundamental		
θ_0	Mean	0.5
σ_0	Variance	1.5
Signal variances		
σ_ε	Private	1.5
σ_η	Public	1.1

Table 7: Parameter values for the benchmark model.

C.4 Figures

D Appendix: Section 4

D.1 Calibration

Table 8 shows the calibrated parameters for the quantitative model.

Firms		
A	Productivity scaler	2.6
α	Capital share	0.3
δ	Depreciation rate	$1 - 0.9^{1/4}$
σ	Elasticity of substitution	3
c	Fixed cost of high capacity	0.021
ω	TFP gain from high capacity	1.0182
Household		
β	Discount factor	$0.95^{1/4}$
γ	Risk aversion	1
ν	Elasticity of labor supply	0.3
Fundamental and signals		
ρ_0	Persistence of θ	0.94
σ_0	Long-run standard deviation of θ	0.027
σ_ε	Standard deviation of private signal	0.001
σ_η	Standard deviation of newspapers	0.001
$\hbar$	Correlation between newspapers (recessions)	0.26
$\hbar$	Correlation between newspapers (expansions)	0.1

Table 8: Parameter values for the quantitative model.

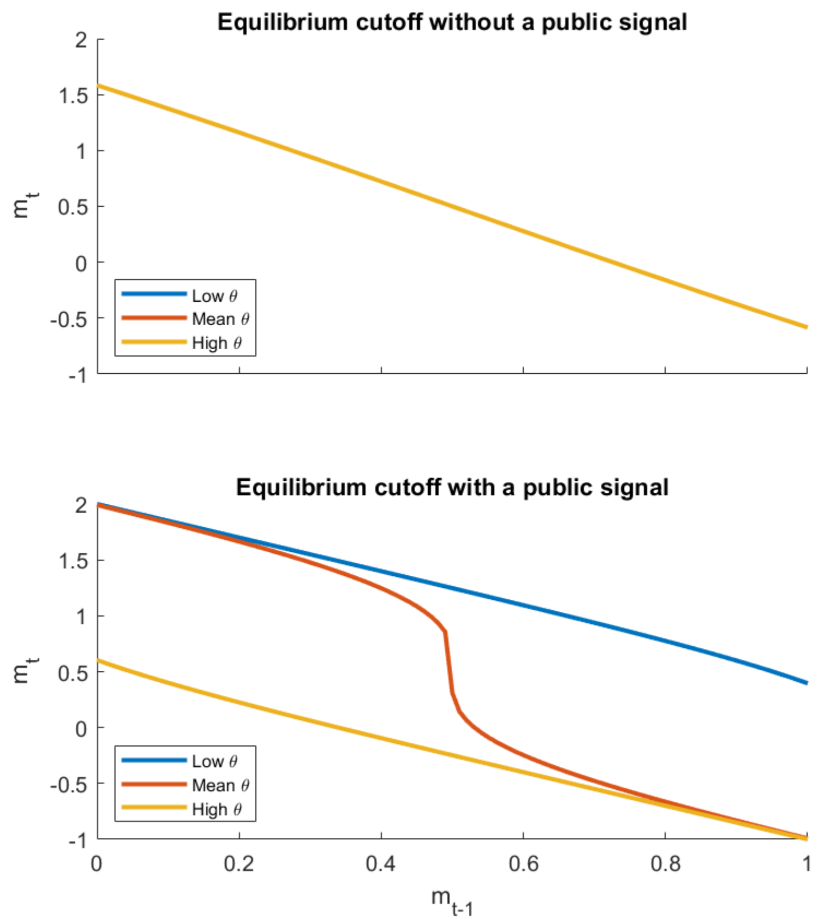

Figure 11: Evolution of the equilibrium cutoff κ_t^* for values of the fundamental, $\theta_t = \{\theta_0 - \sigma_0, \theta_0, \theta_0 + \sigma_0\}$, and for $\eta_t = 0$.