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News Entropy

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Abstract

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We introduce the concept of 'news entropy' to characterise the relationship between news coverage and the economy. Intuitively, news entropy decreases as the news focus on a smaller set of pressing topics. We observe that news entropy exhibits clear negative spikes close to important economic, financial, and political events. Investigating the effect of changes in news entropy, we find that decreases are associated with two key features: an increase in uncertainty measures and a macroeconomic contraction. The variable is priced in the cross-section of stock returns and low news entropy is associated with increased stock price volatility at the firm level.

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1 Introduction

The state of the economy is an integral factor that shapes news coverage. During times of economic and financial crises as well as political uncertainty, the news are likely to cover a smaller set of pressing topics, becoming more concentrated than in normal times. Our understanding of this relationship, however, is limited. In particular, the concept of information in the news is difficult to both conceptualise and measure empirically. Previous research in this area has typically focused on connecting specific terms, topics or sentiments to aggregate economic indicators. This approach, however, is prone to bias, arbitrary linguistic choices and usually suffers from limited generalisability due to underlying changes and differences in languages.

In this paper, we introduce the concept of 'news entropy' to characterise the relationship between the news and the economy. In particular, we first quantify the information communicated by newspaper articles. In doing so we build on an information-theoretic approach to statistical natural language processing. This yields a well-defined measure of news entropy with a number of desirable properties. The underlying intuition is as follows. If the news focus on a small number of topics, news entropy is low. Conversely, news entropy is high in times when the news cover a larger set of topics. In this sense, news entropy can be interpreted as capturing the degree of heterogeneity of news coverage and is related to the newsworthiness of current events.

Estimating the monthly news entropy for full texts of Wall Street Journal articles between 1984 and 2017, we observe that news entropy exhibits clear negative spikes during economic events such as the financial crises in 2008 and 2012, political events, and close to presidential elections. We also find a strong negative correlation with widely used news-based measures such as newsworthiness and policy uncertainty indices. We then empirically investigate the effect of changes in news entropy with respect to the economy. Our results indicate that decreases in news entropy are associated with two key features: a rise in uncertainty and a macroeconomic contraction. Additionally, we demonstrate that news entropy is priced in the cross-section of stock returns, and that low entropy is associated with increased stock price volatility at the firm level.

More specifically, to measure news entropy, we first rely on topic distributions obtained from applying Latent Dirichlet Allocation (Blei, Ng, and Jordan, 2003) to the corpus of Wall Street Journal articles. We then define news entropy as the Shannon entropy (Shannon, 1948) of the monthly topic distributions. Thus, in contrast to other unitless indicators and indices, news entropy is measured in bits – a proper unit grounded in information theory. Note that due to the this construction, news entropy is language-agnostic and thus highly generalisable. In addition to the overall entropy measure estimated for the entire set of news topics, we also estimate the entropy of thematically related subsets – namely cultural, economic and political news.

Examining the relationship between news entropy and other news-based measures, we find that political news entropy is strongly negatively correlated with the concept of news pressure measure by Eisensee and Strömberg (2007). At the same time, we observe no significant relationship of news pressure with economic news entropy, suggesting that top news stories on TV are dominated by political events. We also find that news entropy is negatively correlated with the Economic Policy Uncertainty Index by Baker, Bloom, and Davis (2016) implying that news entropy, while a much broader concept, captures part of the notion of policy uncertainty.

Following Baker, Bloom, and Davis (2016), we then examine the firm-level impact of news entropy using option-implied stock price volatility as a proxy for firm-level uncertainty. We find that firms with higher exposure to government purchases are likely to show increased stock price volatility during periods of low news entropy. Additionally, we observe that news entropy subsumes the effects of both the Economic Policy Index by Baker, Bloom, and Davis (2016) as well as the Chicago Board Options Exchange Volatility Index (VIX) when including all three in the regression specification.

Next, we estimate the macroeconomic impact of news entropy fluctuations by identifying shocks as changes to news entropy which are orthogonal to the state of the economy. Using the local projection method of Jordà (2005), we estimate the impulse responses for a set of key macroeconomic variables and find that a fall in entropy leads to a persistent fall in output and a V-shaped decline in employment which is followed by a subsequent overshoot. The shock is followed instantaneously with a rise in several extant measures of uncertainty.

A third key finding is that news entropy, as well as the economic and political news entropy measures, are a priced risk factor in the cross-section of stock returns. Given that we find decreases in entropy precede periods of severe economic distress, this result aligns with the rare disasters asset pricing model of Barro (2006), Gabaix (2012) and Wachter (2013).

Related Literature. The paper relates to several strands of research. It perhaps most prominently connects to the recent economics literature applying topic models and specifically Latent Dirichlet Allocation by Blei, Ng, and Jordan (2003) to various text data sources. To our knowledge, Mahajan, Dey, and Haque (2008), Fligstein, Brundage, and Schultz (2014), and Hansen, McMahon, and Prat (2017) are the first uses of Latent Dirichlet Allocation in an economics context.

Within this literature, our work is part of a small collection of papers that uses topic models to connect news language to economic activity. For example, similar to our paper, Bybee, Kelly, Manela, and Xiu (2019), Larsen and Thorsrud (2019) and Rauh (2019) use Latent Dirichlet Allocation to analyse news texts. They focus on empirically identifying those topics with the highest predictive power for aggregate economic outcomes. In contrast, our approach is much broader as it does not focus on the shares of specific topics but rather captures structural and behavioural patterns in the news. Nimark and Pitschner (2019) combine empirical observations from topic models with a theoretical framework. They document empirically that two major events increased the homogeneity in coverage across different newspapers devoting more front page coverage to them than to any other topic. News entropy provides a direct measure for this phenomenon as evidenced by our results for Wall Street Journal newspaper articles. Moving beyond the standard topic model, Bertsch, Hull, and Zhang (2021) apply the dynamic embedded topic model to identify economic narratives from Swedish newspaper articles. Using within-topic entropy, they find that the consolidation of narratives is strongly, positively associated with GDP growth over the business cycle. Conversely, they observe that narratives tend to fragment into competing explanations during macroeconomic contractions.

Our focus on newspaper coverage also links our work to Nimark (2014), who illustrates how media coverage of certain events can have definitive business cycle implications. A central principle of the framework developed is that highly concentrated news coverage should cause agents to suffer from higher uncertainty which then spills over detrimentally to output and inflation. This is precisely the result we find empirically, as our identification strategy attempts to separate the portion of news concentration which arises endogenously from the state of the economy. Chahrour, Nimark, and Pitschner (2019) develop a model in which sectoral news coverage can be a substantial contributor to business cycle fluctuations. In a similar vein, Peress (2014) uses newspaper strikes to identify the causal effect of newspaper coverage on financial markets, finding that on strike days, stock market volatility is significantly reduced relative to normal trading days. This would imply that newspaper coverage is a vital component of the propagation mechanism of uncertainty, aligning with our empirical results.

More generally, our paper also relates to the recent economics literature constructing various indices from news language. For instance, the Economic Policy Uncertainty index by Baker, Bloom, and Davis (2016) counts the occurrence of a small set of policy-relevant terms in newspaper texts to measure uncertainty. Another prominent example from the political economy literature is the concept of news pressure by Eisensee and Strömberg (2007) which measures the airtime of the top three segments in news broadcasting. Manela and Moreira (2017) also use machine learning techniques to analyse the content of newspapers, but focus specifically on gauging the perceived risk of a rare economic disaster. Moreover, their analysis only concentrates on the front page of newspapers, whereas our approach is broader.

The remainder is organised as follows. Section 2 introduces the methodology of our news entropy measure and discusses its properties. Section 3 estimates the news entropy series and presents our main descriptive results. Section 4 investigates the relationship between news entropy and the economy from a firm, macroeconomic, and financial prespective. Section 5 concludes.

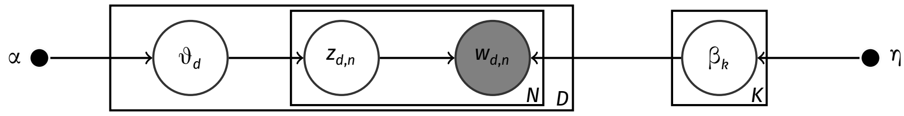


Figure 1. Latent Dirichlet Allocation

Note: Shows the graphical model for Latent Dirichlet Allocation. Shaded variables are observed. Plates indicate replication of the nodes by the number in the lower right corner.

2 Methodological Framework

This section introduces the methodology of our measure. Section 2.1 describes Latent Dirichlet Allocation. Section 2.2 introduces Shannon entropy. This is followed by the definition of our news entropy measure and a discussion of its properties in Section 2.3.

2.1 Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a hierachical Bayesian model for text data (Blei, Ng, and Jordan, 2003). LDA generates documents from distributions over topics. The topics are defined as probability vectors assigning a weight to each word in the vocabulary. That is, a topic is characterised by the set of words that it is most likely to use. Formally, LDA is specified in terms of the following process to generate a set of observed documents:

1. For each document d:
   a. Draw topic proportions $\theta_d | \alpha \sim \mathrm{Dir}(\alpha)$.
   b. For each word $w_{d,n}$:
      i. Draw assignment $z_{d,n} | \theta_d \sim \mathrm{Mult}(\theta_d)$.
      ii. Draw word $w_{d,n} | z_{d,n}, \beta_{1:K} \sim \mathrm{Mult}(\beta_{z_{d,n}})$.

where K specifies the number of topics, $\beta_{1:K}$ are the topic specific word distributions over the vocabulary, and α is a K-dimensional Dirichlet parameter. θ_d represents the topic proportions, z_d denotes the topic assignments, and w_d are the observed words for the d-th document. Figure 1 shows the corresponding graphical model.

To put this in words, each document is endowed with a Dirichlet-distributed vector that specifies the topic proportions. For each word in the document corpus, the model draws a topic assignment based on the topic proportions. Finally, the topic assignment is then used to generate the word. Note that this modelling approach implies that a word can be used for multiple topics with different probabilities. There is a variety of inference procedures for parameter estimation including sampling and optimisation based algorithms.

2.2 Shannon Entropy

The Shannon entropy (Shannon, 1948) of a random variable X is defined as

$$H(X) = -\sum_{i=1}^{N} p(x_i) \log_2 p(x_i),$$

where N is the number of possible outcomes and $p(x_i)$ is the probability of the outcome x_i. This can also be written as $H(\boldsymbol{p})$, where $\boldsymbol{p}$ is a vector of probabilities $(p_1, p_2, \ldots, p_N)$. When using a logarithm with base two, Shannon entropy is measured in bits.

There are many interpretations of entropy. From an information-theoretic perspective, entropy measures the amount of information that a random process carries about the outcome. It can also be interpreted as a measure of the uncertainty in a process. That is, it represents the uncertainty regarding the realisation of the random variable. In this paper, we rely on entropy to measure the degree of heterogeneity of a probability distribution. In particular, a decrease in entropy decreases the heterogeneity – or increases the homogeneity – of the random variable's outcomes.

Shannon entropy has the following properties. First, it is continuous with respect to the probabilities of the outcomes. Second, it is symmetric with respect to the order of the probabilities. Third, it is maximised when all probabilities $p(x_i)$ are equal. The maximum is equal to $\log_2(N)$. Fourth, the entropy of a process is equal to zero if all but one probability $p(x_i)$ are equal to zero. Fifth, if a process be divided up into successive processes, the original entropy is equal to the weighted sum of the individual entropies. We provide an interpretation of these properties in the context of our application in the following section.

2.3 News Entropy

Based on the definition of LDA and Shannon entropy, we now construct our measure of news entropy. From an information-theoretic perspective, each topic distribution in the generative model of LDA represents a source that produces a signal (Murdock, 2019). The signal is the stream of words forming the document. In this context, we define news entropy as the entropy of the topic distribution

$$\mu_d = H(\theta_d).$$

That is, μ_d represents the degree of heterogeneity of the outcomes of the process described by the topic distribution. Alternatively, news entropy can also be interpreted as a measure of uncertainty regarding the topic a word was generated from.[1]

1. When viewed as the uncertainty of the reader regarding the topic assignment the next word in the newspaper article, news entropy connects to the first use of entropy applied to natural language by Shannon (1951).

The underlying intuition of news entropy is as follows. When an important event occurs, the news will dedicate a large share of their coverage to the event in question. In other times, when no major news event has occurred, the news instead cover several minor events. Assuming that different types of events can be represented by news topics, newspaper texts will be dominated by fewer topics during major events compared to normal times and secondary news are crowded out. In this sense, news entropy captures the degree of heterogeneity of news coverage and is related to the newsworthiness of current events.

Further Properties. We now derive further properties of our measure. First, due to the continuity property of Shannon entropy, small changes in the topic shares result in small changes to the overall information. As a result, there are no discontinuous jumps in news entropy as the newspaper increases or decreases its focus on a particular topic.

Second, news entropy is invariant to changes in the ordering of topics inferred from LDA. This is a necessary condition for a proper measure both from a statistical and economic perspective. In particular, the ordering of topics might differ between different runs of the LDA algorithm on the same data. This is due to the random sampling as part of the computational inference procedure. As long as the inferred probabilities are the same, however, news entropy does not change. That is, we implicitly assume that the order in which the reader learns about the topics does not affect their information processing. Further, this implies that the topics' information shares are independent of each other. This independence assumption relates to the underlying assumption in the LDA model that topics are uncorrelated.[2]

Lastly, as stated above, entropy satisfies the following property: if a process is divided up into successive processes, the original entropy is equal to the weighted sum of the individual entropies. This can be interpreted as the "coarse-graining" property (Dedeo, 2018). The coarse-graining property of entropy has three major implications for our application to topic distributions. First, specifying a larger number of topics in the LDA model results in higher news entropy since more information needs to communicated. Second, the entropy of topic subsets after renormalising the topic shares will be smaller than the entropy for the whole set of topics. Third, for a given number of topics, we can coarse-grain the topic shares to calculate news entropy based on thematically related groups of topics. This is important since it allows to independently estimate the topic model with the number of topics set to be statistically optimal or provide the most intuitive interpretation of topics. This is then followed by calculating the entropy at the desired level of coarse-graining. This emphasises the flexibility and general applicability of our approach.

2. This is due to the independence assumption implicit to using Dirichlet distributed topic proportions. Under the Dirichlet, the topic shares are nearly independent. As a result, the presence of one topic is not correlated with the presence of another. To allow for a covariance structure between topics, Blei and Lafferty (2007) have developed the Correlated Topic Model.

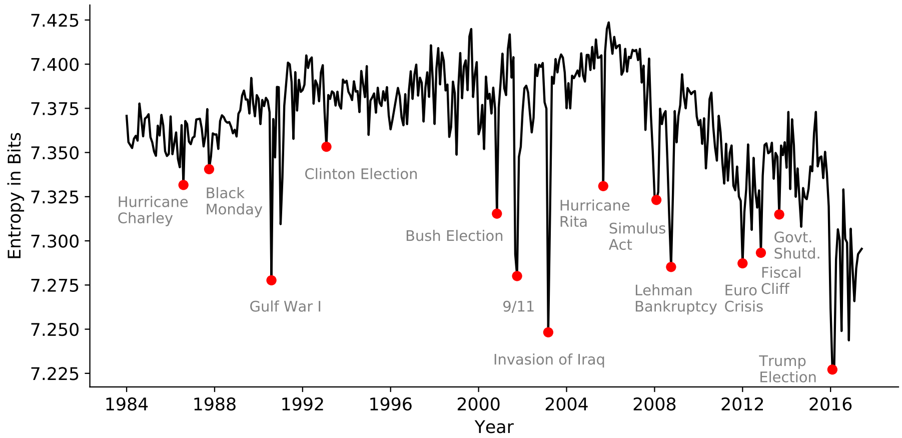


Figure 2. News Entropy.

Note: This figure shows news entropy from 1984 to 2017.

3 Estimation

This section estimates news entropy and presents our main descriptive results. Section 3.1 describes our original data sources. Section 3.2 describes the estimated entropy series and connects them to major events. Section 3.3 compares news entropy to existing measures of news pressure and policy uncertainty.

3.1 Data

We rely on the pre-trained LDA topic vectors for the Wallstreet Journal (WSJ) provided by Bybee et al. (2019). The data set consists of the monthly topic vectors estimated from the full newspaper texts of 763,887 articles published between January 1984 and June 2017. The vocabulary comprises 18,432 uni-grams and bi-grams. For content consistency, articles published in sections other than the three core sections (“Section One,” “Marketplace,” and “Money and Investing”) are excluded. In addition, articles with predominantly non-economic tags as well as regular data tables are excluded. The number of topics in the LDA model was set to 180 based on statistical goodness-of-fit criteria. Bybee et al. provide a data-driven hierarchy of increasingly broad meta-topics based on the semantic distances between topics. At the broadest level, the hierarchy distinguishes between “economy” topics and “politics and culture” topics. The macroeconomic data comes from the FRED-MD database of McCracken and Ng (2016). We obtain firm-level data from Baker, Bloom, and Davis (2016).

Table 1. Correlations.

	News Entropy	NE (econ.)	NE (poli.)	NE (cult.)	News Pressure	EPU
News Entropy	1.00					
NE (econ.)	0.55	1.00				
NE (poli.)	0.87	0.13	1.00			
NE (cult.)	0.47	0.33	0.28	1.00		
News Pressure	-0.38	0.02	-0.52	0.05	1.00	
EPU	-0.55	-0.32	-0.50	-0.19	0.39	1.00

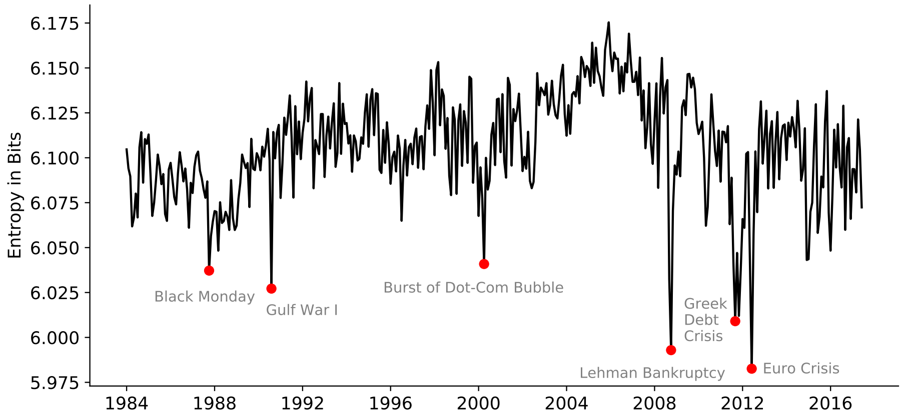
Notes: This table presents correlation coefficients between each of the four news entropy series, News Pressure, and the Economic Policy Uncertainty (EPU) index.

3.2 Descriptives

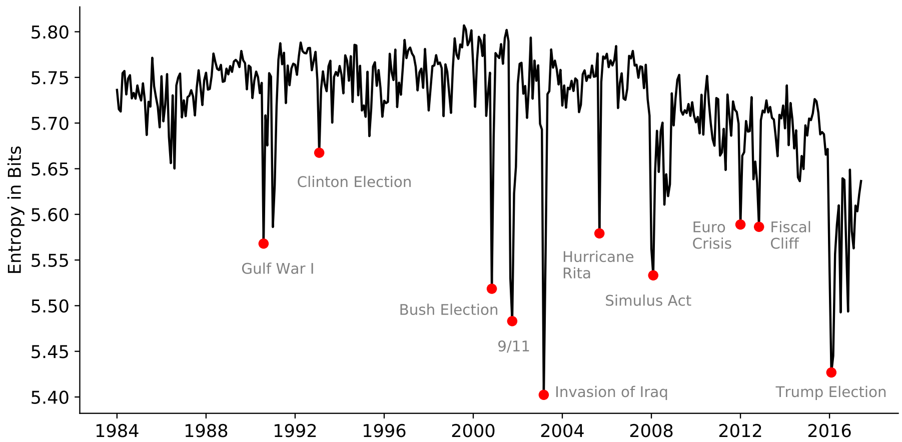
We calculate news entropy from the pre-trained WSJ topic distributions. Figure 2 shows the resulting time series from 1984 to 2017. The graph exhibits clear negative spikes during events related to the financial crises in 2008 and 2012, the Gulf and Iraq War, political events such as the US government shutdown in 2013, natural disasters, after the 9/11 terrorist attacks, and close to presidential elections. Strikingly, there seem to be both increased volatility levels and a general downward trend in news entropy starting from 2000 with the 2016 presidential elections representing the overall minimum of the time series.

Next, we construct news entropy measures for thematically related topic subsets. Specifically, based on the topic taxonomy provided by Bybee et al. (2019), we select topics falling into the three broadest categories: economics, politics, and culture. They consist of 77, 59 and 44 topics, respectively. We separately renormalise the topic probabilities for each category and then compute the individual news entropy series. Figure 3 shows the respective graphs. We see that the entropy of these subsets picks up the different events seen in the overall graph. More specifically, the news entropy for the economics subset spikes during events such as Black Monday and the Lehman Bankruptcy. Interestingly, the burst of the dot-com bubble is not visibly picked up by overall news entropy while the economic news entropy series shows a clear negative spike. As expected, political news entropy spikes during events such as presidential elections. Lastly, the culture news entropy series is very noisy and does not seem to pick up any significant events.

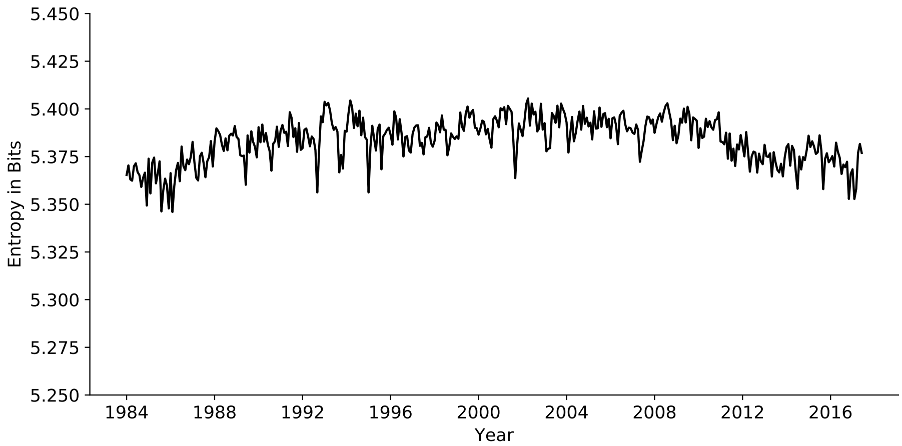
While it may be assumed that the four entropy series are all highly correlated with each other as they might predominantly capture common factors, Table 1 shows this is not the case. The only two series which are highly correlated are the main entropy series and the political entropy series, highlighting the dominance of the political news cycle. All other series are positively correlated, but have substantially lower correlation coefficients and thus represent distinct information.



(a) Economics News



(b) Politics News



(c) Culture News

Figure 3. News Entropy for Topic Subsets.

Notes: The figure shows the news entropy series for different topic subsets.

An interesting immediate result is the downward trend in the series which begins following the onset of the financial crisis. Using a Quandt likelihood ratio test (Andrews (2003)) to detect an unknown structural break date, we find one in August 2008. Repeating this procedure for the political entropy measure also results in a structural break being detected in 2008, although the break occurs earlier in the January of that year. We do not find similar evidence of a structural break in the 21st century for the economics or culture series. This result could be interrogated much further, but suggests that news coverage has become more concentrated on a smaller set of dominant topics since the Great Recession, especially with respect to political discourse.

3.3 News Entropy, News Pressure and Policy Uncertainty

News Pressure. We compare news entropy to the concept of news pressure by Eisensee and Strömberg (2007). News pressure measures the amount of airtime a news broadcast allocates to the top three news segments in a day. Specifically, it is defined as the median number of minutes devoted to the first three news segments across broadcasts in a day. The underlying intuition is that the top three news segments represent the most newsworthy events on a given day. Thus, on days of high news pressure – that is, longer airtime for the top three news stories – there is a large amount of newsworthy material and important events dominate the news. Eisensee and Strömberg (2007) show that in turn secondary news get crowded out and receive less coverage. Furthermore, recent applications of news pressure in the field of political economy have shown, for example, that higher news pressure correlates with the likelihood of military attacks (Durante and Zhuravskaya, 2018) and US presidential executive orders (Djourelova and Durante, 2020).

One drawback of news pressure is that it heavily relies on the structure of news broadcasting. In addition, there is no corresponding measure for text-based news reporting. In this context, news entropy provides an alternative measure for newsworthiness based on unstructured news data. Table 1 shows the correlations between news pressure and our four news entropy series. We find that news pressure is most strongly correlated with the political news entropy series with a correlation of -0.52. As expected, it is therefore moderately correlated with the overall news entropy series. Interestingly, there is no significant correlation between news pressure and economic news entropy. This result is rather intuitive as it suggests that economic news are rarely part of the top three news segments on TV. Moreover, we observe that there is no significant correlation between news pressure and the culture news entropy series. Hence, this implies that top news stories on TV are dominated by political events. In future applications, our method could be applied to directly compute the entropy of TV news transcripts.

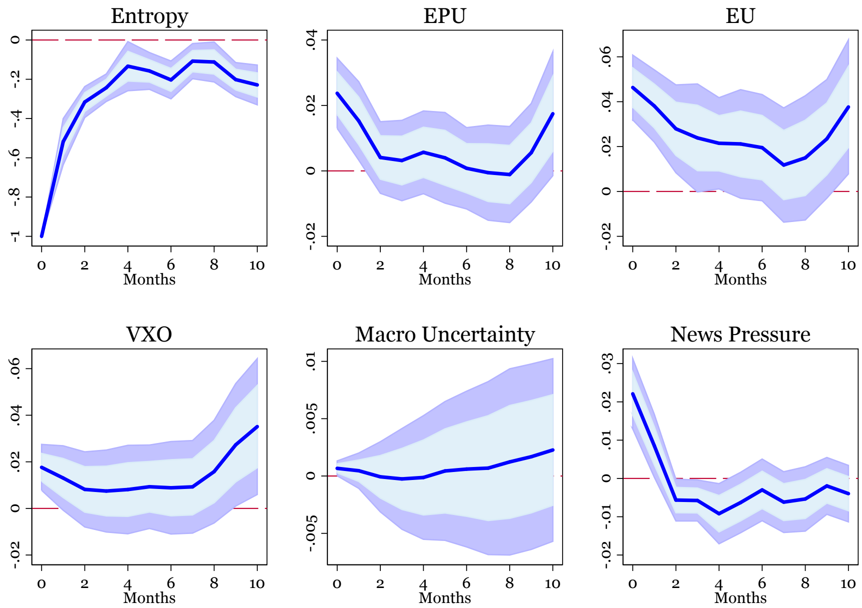


Figure 4. Responses of Other Measures to a Fall in Entropy.

Note: The figure shows the impulse response functions of the different measures to a news entropy shock. The light (dark) blue shaded area represents the 68% (90%) Newey-West adjusted confidence intervals.

Policy Uncertainty. Next, we investigate the relationship between news entropy and the Economic Policy Uncertainty (EPU) Index by Baker, Bloom, and Davis (2016). The EPU is an index constructed based on the frequency of the words "uncertain" or "uncertainty" and "economic" or "economy" in newspaper articles in combination with six other policy relevant terms. Similar to our results, Baker, Bloom, and Davis (2016) find that the EPU index spikes near major policy-relevant events. Further empirical applications of the EPU include, for example, Gulen and Ion (2016) who provide evidence of a strong negative relationship between firm-level capital investment and the aggregate level of uncertainty.

As documented in Table 1, we find that the EPU index and news entropy move in opposite directions with a correlation of approximately -0.55. This suggests that economic uncertainty increases as news entropy decreases. The same holds for the economic and political news entropy series. Interestingly, the correlations of news entropy and political news entropy do not differ much, implying that mostly politics news are associated with policy uncertainty. The correlation between the cultural news entropy series and the EPU is significantly weaker. It is worth noting that there is a positive correlation between the EPU index and news pressure suggesting that as the frequency of newspapers mentioning uncertainty is associated with longer coverage of the top three stories in TV news broadcasting.

Impulse Responses. To further investigate the relationship between news entropy and commonly used economic uncertainty measures, we rely on the local projection method of Jordà (2005) and include four series as dependent variables: the EPU, the S&P 100 Volatility Index (VXO), and the macroeconomic uncertainty series from Jurado, Ludvigson, and Ng (2015). We directly estimate the impulse response functions via a local projection method which will be explained in more detail subsequently. In our specification, we allow the uncertainty measures to respond contemporaneously to the shock so as not to defeat the object of the exercise. The contemporaneous value of industrial production as well as lags are included, meaning that the shock is identified as a change in entropy that is orthogonal to output. Figure 4 shows the results. The VXO, economic and economic policy uncertainty indexes and the news pressure index all display a rise upon impact of the shock and we can reject the null hypothesis of zero impact coefficients for these series at the one percent level. Thus there seems to be a clear link between entropy and economic uncertainty as we argued previously. The macroeconomic uncertainty index does not respond to any significant degree. Just like the dynamics of entropy, the majority of the series return back to steady state very quickly.

4 Economic and Financial Impacts

This section investigates the relationship between news entropy and the economy at the firm, macroeconomic, and financial levels. Section 4.1 analyses the impact changes in news entropy at the firm-level. Section 4.2 examines the effects of news entropy shocks on and important macroeconomic indicators. Section 4.3 examines the relevance of news entropy to asset pricing.

4.1 Firm-Level Impact

We examine the firm-level impact of news entropy using option-implied stock price volatility as a proxy for firm-level uncertainty. The data sample contains 136,578 observations on 5,460 firms from 1996 to 2012 obtained from Baker, Bloom, and Davis (2016). Table 2 shows the results of quarterly 30-day implied stock price volatility regressed on quarterly average news entropy using firm sales as weights. Columns (1) to (5) rely on the same baseline identification strategy as Baker, Bloom, and Davis (2016) and adopt their measure of firm exposure to uncertainty about government purchases of goods and services.

The specification in column (1) regresses the log of 30-day implied volatility on the logarithm of news entropy. Additionally, the ratio of federal government purchases to GDP is included as a policy control. The coefficient of logged news entropy is highly statistically significant. In this specification, a one percent decrease in news entropy connected to a 21.59% increase in implied volatility. We find that

Table 2. Option-Implied Stock Price Volatility and News Entropy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(Entropy)	-21.585***			2.651**					
	(0.995)			(1.04)					
Log(Entropy) × Intensity			-27.098***		-25.549***	-22.022***			
			(7.568)		(8.167)	(7.335)			
Log(VIX)				0.715***					
				(0.013)					
Log(VIX) × Intensity					0.044	0.007			
					(0.09)	(0.115)			
$\frac{\text{Federal Purchases}}{\text{GDP}}$	-14.214***	-19.3***		-8.139***					-14.227***
	(1.531)	(1.5)		(1.481)					(1.531)
$\frac{\text{Federal Purchases}}{\text{GDP}}$ × Intensity			-30.9**		-30.629**	-31.397***	-29.416***	-30.081***	
			(12.421)		(12.309)	(12.131)	(12.389)	(12.335)	
Log(EPU)		0.432***							
		(0.010)							
Log(EPU) × Intensity						0.074		0.094	
						(0.089)		(0.066)	
Log(Entropy Economics) × Intensity							-30.371***	-27.569***	
							(5.55)	(5.343)	
Log(Entropy Politics) × Intensity							3.031	4.986***	
							(1.882)	(1.666)	
Log(Entropy Culture) × Intensity							-17.077	-18.215	
							(21.375)	(21.216)	
Standardised Entropy									-0.08***
									(0.004)
Firm and Time Effects	No	No	Yes	No	Yes	Yes	Yes	Yes	No

Notes: Dependent variable: natural log of the 30-day implied volatility for the firm, averaged over all days in the quarter. The sample is taken from Baker, Bloom, and Davis (2016) and contains 136,578 observations on 5,460 firms from 1996 to 2012. Intensity is a firm's exposure to federal purchases of goods and services. All regressions are weighted by a firm's average sales. Standard errors are clustered by firm.

an increase in the ratio of federal purchases to GDP is associated to lower volatility. Column (2) shows the results obtained by Baker, Bloom, and Davis (2016) using the logarithm of the EPU index. Column (3) includes firm and time fixed effects. Additionally, this specification interacts news entropy with firm-level exposure to government purchases. This specification yields a strong relationship between news entropy and implied volatility for firms with greater exposure to government purchases. Column (4) includes the Chicago Board Options Exchange Volatility Index (VIX) in the regression specification. This results in a sign reversal for the news entropy coefficient and a highly significant VIX coefficient. As noted by Baker, Bloom, and Davis (2016) in case of the EPU, this is expected as the VIX measures the 30-day implied volatility on the S&P500 index and should thus be strongly related to the average 30-day implied volatility for publicly listed U.S. firms. Column (5) includes firm and time fixed effects and interacts all regressors with firm-level exposure to government purchase. We find that intensity adjusted news entropy has highly statistically significant coefficent that is larger in magnitude compared to the baseline specification in column (1). We observe that the coefficient on the VIX is statistically indistinguishable from zero. This allows us to draw the same conclusion as the one by Baker, Bloom, and Davis (2016) with respect to the EPU: the VIX has the largest explanatory power for the average firm's 30-day implied volatility. Once we account for exposure to government purchases, however, news entropy explains a significant part of firm-level implied volatility. In summary, the results from running the baseline specifications using news entropy as a predictor for option implied stock price volatility in columns (1) to (5) mirror the findings from Baker, Bloom, and Davis (2016).

In addition, we confirm the above findings using a second set of regressions. Column (6) runs the same specification as column (4) with firm and time fixed effects as well as exposure to government purchase but additionally includes the EPU. The news entropy coefficient is significant and of similar magnitude as in the previous specifications. Strikingly, both the coefficient of the EPU and the VIX are statistically indistinguishable from zero while the news entropy coefficient is highly significant. This observation indicates that when comparing the three measures to each other in a setting where we take into account government exposure, news entropy subsumes the effects of the other two, which is in line with its construction as a broader measure. Column (7) simultaneously includes the entropy of the three news subcategories economics, politics and culture in combination with fixed effects and government exposure in place of the general news entropy. We observe that only the economics entropy series has a statistically significant relationship with stock price volatility. Column (8) includes the EPU as a control. The resulting coefficient is not significant. Interestingly, the coefficient of the politics news entropy series is now statistically significant with a positive coefficient. That is, once we control for the use of the words such as "uncertainty" as measured by the EPU, stock price volatility increases in political news entropy. Finally, we note that when using the logarithm of news entropy, a one percent change in news entropy is rather large looking at the entire time series. This is in contrast to the EPU as the EPU is a normalised unitless index while entropy is measured in bits. To test whether this affects our results, we provide an alternative specification where we measure the effect of a one-standard-deviation change in news entropy. While we find that the resulting coefficient is much smaller in magnitude as expected, it is highly statistically significant. At the same time, the coefficient of the ratio of federal government purchases to GDP is virtually unchanged. Hence, this indicates that our results do not depend on the normalisation method and confirms the above findings.

4.2 Macroeconomic Impact

We now investigate the relationship between important economic indicators and news entropy. As a preliminary exercise, we look at the cyclical properties of the set of measures by examining the correlation of each with industrial production (IP). After each series is detrended with a Hodrick-Prescott filter (with a smoothing parameter of 129,600), the correlation between the main entropy series and the log of IP is a mere 0.03 and is not statistically significant at conventional levels. Interestingly, the series is therefore acyclical. This is a notable difference from the EPU, which exhibits strong and significant countercyclicality, with a correlation coefficient of -0.35 with the log of IP. The topic entropy measures also all display a lack of any kind of cyclical pattern – the politics measure is the only series whose correlation coefficient is statistically significant.

Next, we use the local projection method of Jordà (2005) to fully explore the macroeconomic impacts of a shock to the entropy measure, directly estimating the impulse response functions (IRFs). See Plagborg-Møller and Wolf (2019) for a full review of this approach as well as its similarities and differences with the structural vector autoregression (SVAR) approach. The specification for the local projection can be expressed as

$$Y_{t+h} \;=\; \alpha_h + \gamma_h e_t + \psi_h(L) Z_t + u_{t+h}$$

where Y is an endogenous variable of interest, e_t is the main entropy measure in period t and Z_t is a set of control variables. The endogenous variables we investigate include industrial production, non-durable consumption and services, durable consumption, initial claims for unemployment insurance, hours worked, the consumer price index (CPI) and the shadow Federal Funds rate from Wu and Xia (2016). All variables except the last enter in log levels. The set of controls in each regression includes six lags of the entropy measure, the current value and six lags of the dependent variable and the current value and six lags of industrial production. A linear trend is also included. As shown by Plagborg-Møller and Wolf (2019), this procedure is equivalent to ordering the entropy measure last in a recursively ordered SVAR and can be considered conservative as such. The entropy measure is standardised to have

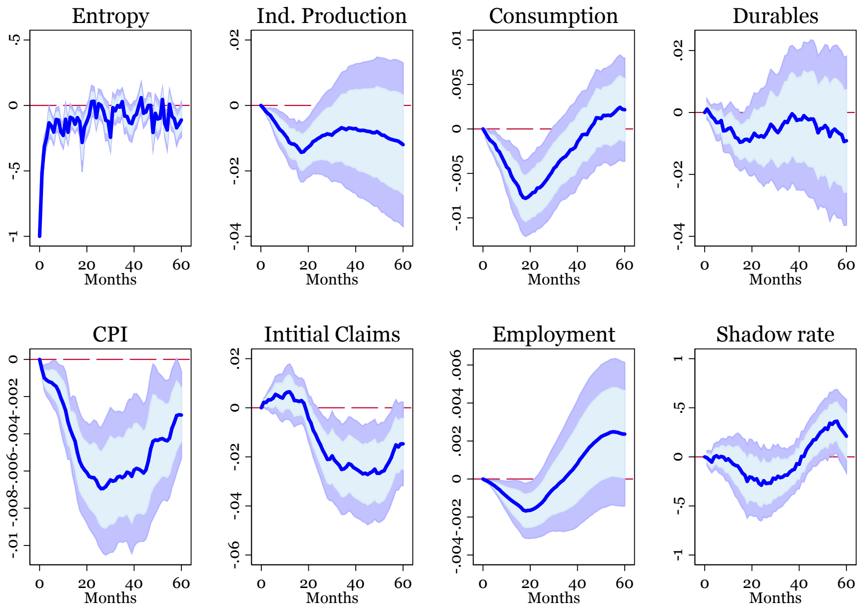


Figure 5. Responses to News Entropy Shock.

Note: The figure displays the estimated impulse response functions of the endogenous variables for a shock to the entropy measure. The light (dark) blue shaded area represents the 68% (90%) Newey-West adjusted confidence intervals.

a mean of 0 and a standard deviation of 1 and we examine a negative shock, that is, a fall in entropy. The maximum value of h is set at 60 for a five-year horizon for the IRFs. To correct for serial correlation in the errors, Newey-West standard errors are employed with automatic bandwidth selection (Newey and West, 1994). The sample period is from January 1984 to June 2017.

Figure 5 displays the estimated impulse response functions for the endogenous variables along with one standard error confidence bands. Entropy decreases but bounces back almost immediately and does not persistently stay below trend. The shock is contractionary, with output remaining persistently below steady state afterwards. The recession is particularly concentrated in non-durable consumption and services, which exhibits a v-shaped decline, and is also accompanied by a clear decline in the price level. The decline in both of these variables is precisely estimated. Durable consumption falls although the estimates are imprecise. Initial claims increase, indicating a rise in layoffs, while employment falls. This decrease in employment is followed by an overshoot after around three years, mirroring the same pattern found in Bloom (2009) after an uncertainty shock. The shadow Fed. Funds rate falls slightly, which suggests that the Federal Reserve responds according to its Taylor rule in an attempt to counteract the impact by cutting interest rates.

To ensure the contractionary effect of a decrease in entropy is a robust result, we also estimate impulse response functions from an array of modified specifications which include:

- Hodrick-Prescott filtered variables with a smoothing parameter of 129,600.
- three lags of all variables.
- twelve lags of all variables.
- lags of stock prices as an additional control variable.
- lags of the VXO as an additional control variable.
- the contemporaneous value and lags of employment as an additional control variable.
- using a different causal ordering equivalent to ordering the entropy measure first in a recursively identified SVAR.

The estimated impulse response functions for each of these alternative specifications is presented in Figure 6. The contractionary response remains present in all specifications, and most of them yield extremely similar estimates to the baseline specification. Using a Horick-Prescott filter results in industrial production displaying the overshoot pattern exhibited by employment, while the addition of employment as a control variable slightly attenuates the response after the 18 month horizon.

We next investigate shocks to the topic-specific measures of entropy. The estimated IRFs can be found in Figure 7. The main finding from these is that shocks to the political and economic entropy series are also contractionary, and lead to a qualitatively similar (but quantitatively smaller) decline in industrial production. The response of consumption and the monetary policy variable is particularly pronounced for the economic series.

We also look at large changes in entropy by defining an indicator variable that takes the value of 1 when the entropy measures is more than one standard deviation below its mean. 58 such months in the sample are classified as low entropy periods. We then include this indicator in the local projection, keeping the rest of the specification the same. The estimated IRFs for this shock are shown by Figure A.1 in Appendix A. They closely resemble the benchmark IRFs, with a contraction occurring as well as notable deflation.

Nonlinear Effects. Next, we further our analysis by exploring whether there are nonlinearities present in the impulse responses of the macroeconomic variables to an entropy shock. We have previously noted that many of the large decreases in the news entropy measure corresponded to natural or economic disasters such as Black Monday, 9/11 and the collapse of Lehman Brothers. A natural question that arises is then whether larger news entropy shocks have a disproportionate impact on the macroeconomy. To investigate this, we run the following specification of the local projection with the same set of dependent variables as previously:

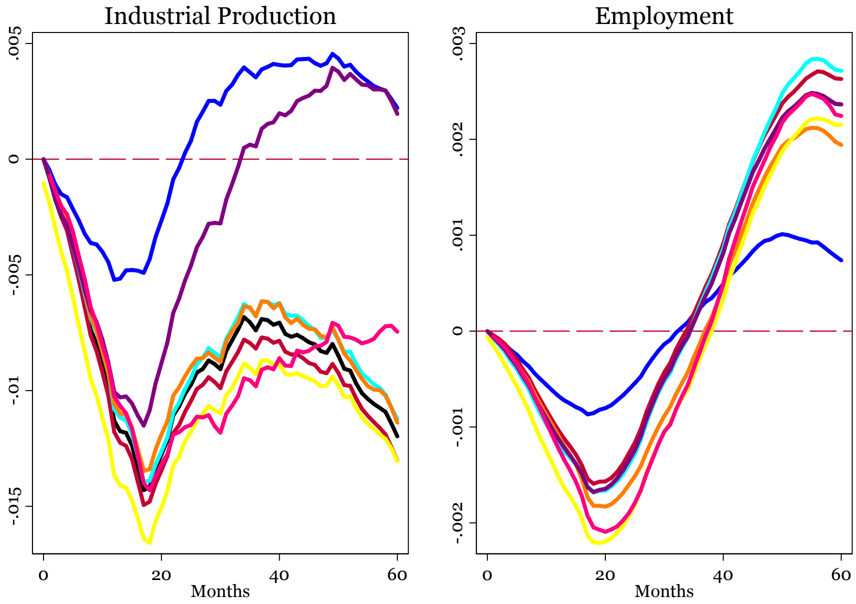
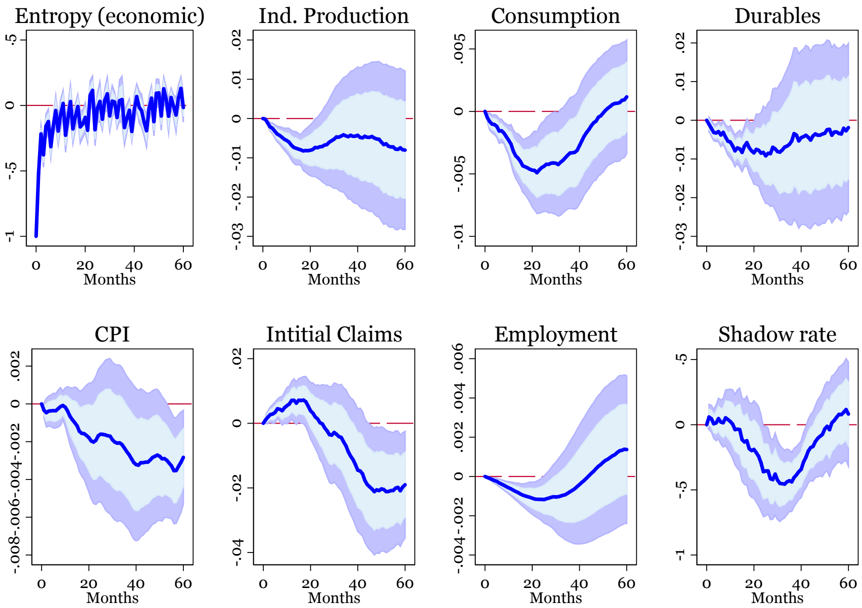


Figure 6. Robustness Tests for the News Entropy Shock.

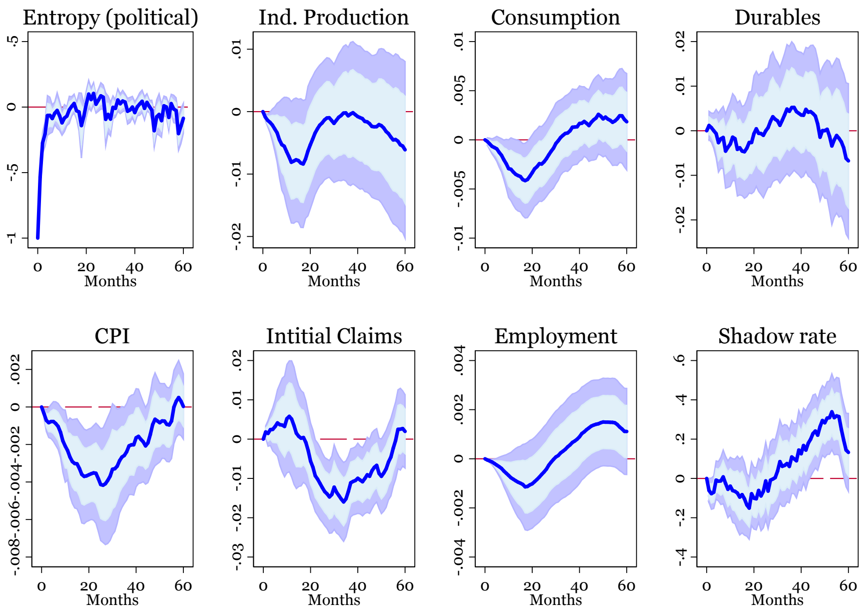
Note: The figure shows the estimated impulse response functions from alternative specifications represented by different colours in addition to the baseline specification (black) which include: Hodrick-Prescott filtered variables (blue), three lags of all variables (dark red), twelve lags of all variables (cyan), stock prices as a control (orange), lags of the VXO as an additional control variable (pink), employment as a control (purple). The yellow line displays the estimates from the specification with an alternative causal ordering.

$$Y_{t+h} = \alpha_h + \gamma_h e_t + \bar{\gamma}_h e_t^2 + \tilde{\gamma}_h e_t^3 + \psi_h(L) Z_t + u_{t+h}$$

We therefore allow for nonlinearities in the impulse response function via the inclusion of the quadratic and cubic terms in the shock. We compare these IRFs estimated from the nonlinear LP to those estimated from the benchmark linear specification in Figure 8. This clearly illustrates the presence of nonlinearities, as substantial deviations between the two IRFs are present. Crucially, the response of entropy in the two specifications is very similar. A key difference in IRFs the nonlinear specification is the tendency of most variables to display a sharper contractionary movement than in the linear case, but then a rebound that involves a sizeable expansion after around two years. For example, in the linear specification, the estimate IRF for layoffs (as measured by initial claims for unemployment insurance) is more or less flat over the horizon period, whereas in the nonlinear specification the variable displays a large rise in response to the shock, which is then followed by a substantial fall. A similar phenomenon is present in Bloom (2009), who also estimates this rebound for many variables after an uncertainty shock. Another key difference is that the



(a) Responses to Economic News Entropy Shock.



(b) Responses to Political News Entropy Shock.

Figure 7. Responses to Entropy Shock of News Themes.

Notes: The figures show the impulse response functions for economic and political news entropy shocks. The light blue shaded area represents the 68% Newey-West adjusted confidence intervals. The dark blue shaded area represents the 90% Newey-West adjusted confidence intervals.

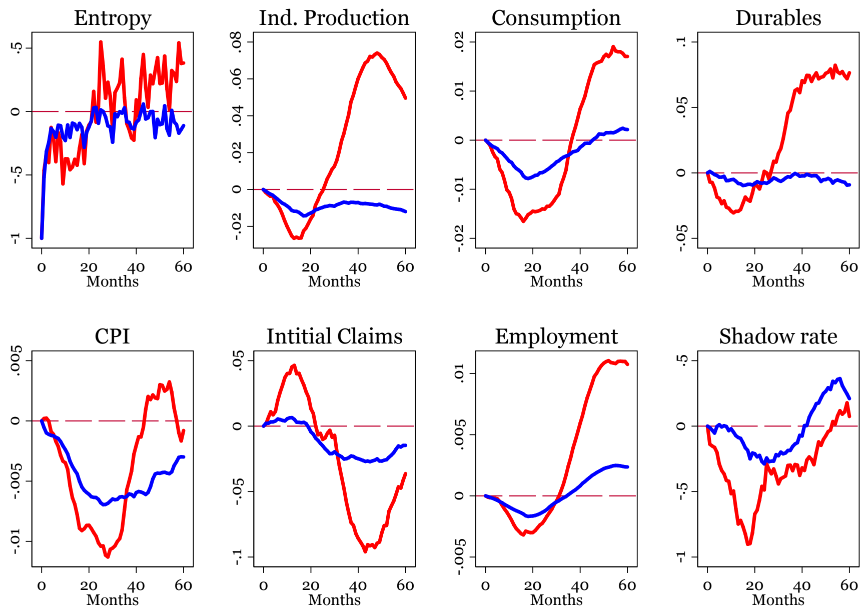


Figure 8. Impulse response functions from nonlinear local projections

Note: The red line in each figure corresponds to the impulse response function estimated from the specification which includes higher order terms of the shock. The blue line in each figure corresponds to the benchmark specification which is linear in the shock.

response of monetary policy is found to be much more pronounced in the nonlinear specification. This may suggest that the Federal Reserve is taking more drastic action in response to these disasters, as was the case with Quantitative Easing (QE) during the financial crisis.

4.3 Financial Impact

Next, we investigate the relevance of our news entropy variable in an asset pricing context. Specifically, we pose the question: is news entropy priced in the cross-section of returns? To do this, we implement the canonical method of Fama and MacBeth (1973) to estimate linear factor models. Let J denote the total number of portfolios and T denote the total number of time periods used in the estimation. The procedure involves first running J time-series regressions of the form

$$R_t^{e,j} = a_j + \beta_j f_t + \epsilon_t^j \qquad\qquad j = 1, \ldots, J$$

where $R_t^{e,j}$ is the excess return (over the risk-free rate) of asset j in period t and f_t is a $K \times 1$ vector of factors. The second step of the procedure estimates the risk

Table 3. Fama and MacBeth (1973) Regressions.

λ_{NE}	$\lambda_{\mathrm{NE(econ.)}}$	$\lambda_{\mathrm{NE(poli.)}}$	λ_{R^M}	λ_{SMB}	λ_{HML}	MAPE
0.079						1.39
(4.32)						
	0.034					1.42
	(4.26)					
		0.301				2.79
		(4.37)				
			0.917	0.028	0.326	0.99
			(4.13)	(0.18)	(2.17)	

Notes: The table reports results of Fama and MacBeth (1973) regressions for the 25 Fama-French portfolios. See text for full estimation details. MAPE denotes the mean absolute pricing error. Square brackets denote t-statistics. The sample period is from January 1984 to June 2017.

price for each factor by using the first-stage estimated factor loadings and running T cross-sectional regressions

$$R_t^{e,j} = \lambda_t \hat{\beta}_j + \alpha_t^j \qquad t = 1, \ldots, T$$

The estimated risk factor prices are then given by

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \lambda_t.$$

As test assets, we follow the majority of the literature and use the 25 Fama and French (1993) portfolios sorted by size and book-to-market. We estimate three single-factor models with the main news entropy measure, the economic news entropy measure and the political news entropy measure. As a benchmark with which to draw a comparison, we also estimate the Fama and French (1993) three factor model with the excess return on the market portfolio, the size premium (SMB) and the value premium (HML). We report the estimated risk prices from each model as well as the t-statistics. Additionally we also report the mean absolute pricing error from each model, which indicates how effectively each model can explain the overall cross-section of returns.

Table 3 displays the results from the Fama-MacBeth regressions. The first notable result is that all three entropy measures display positive risk prices which are statistically significant at conventional levels. Assets which are more exposed to the news cycle earn a risk premium. For the main news entropy measure, a one standard deviation in exposure (β) is associated with a 3.04 percentage point increase in the annualised expected excess return on an asset. This value is very similar for the economic news entropy measures at 2.44 percentage points. Interestingly, for the political news entropy it is more than double at 5.36 percentage points. The pricing errors are lowest for the main news entropy single-factor model, although they

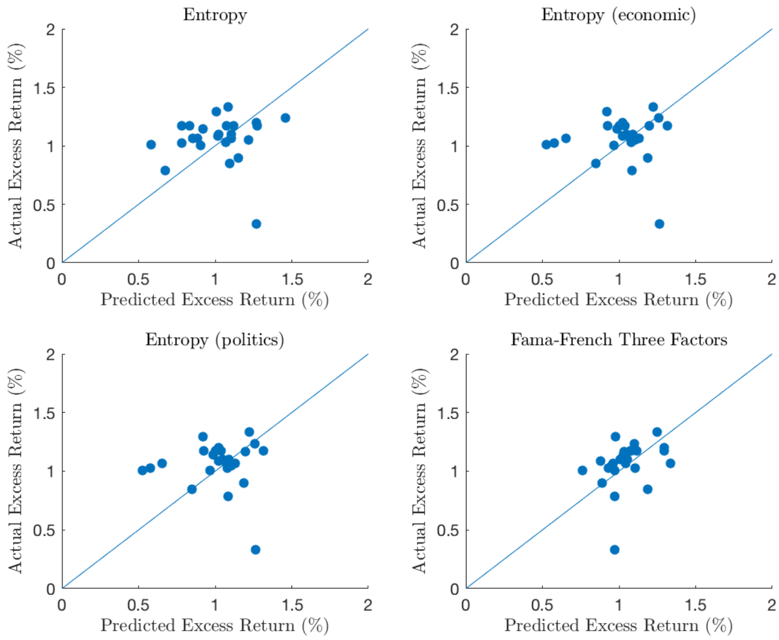


Figure 9. Fama-MacBeth Plots

Note: The figure plots the predicted excess return for each of the 25 Fama-French portfolios against its sample average excess return for each of the four factor models.

remain low across all three models. Comparison to the three-factor Fama-French model estimates reveals that the entropy models are able to achieve a comparable level of performance, with only slightly higher pricing errors.

Figure 9 plots the predicted excess return on each portfolio from each of the four factor models against the actual expected excess return. This further illustrates the success of the news entropy factor models, as the pricing error for most portfolios is low. All four models struggle to successfully price the small growth portfolio in this sample period.

5 Conclusion

We have introduced the concept of news entropy to parsimoniously characterise the complex structure of news content in simple terms. Empirically, we find that news entropy features negative skewness and positive kurtosis, as it collapses during times of significant political and economic unrest as well as natural disasters such as hurricane Rita. We find that these decreases in news entropy coincide with periods of high uncertainty, and results from local projections demonstrate that they are followed by a macroeconomic contraction. Meta-topic specific analysis shows that economic news entropy has a particularly strong association with these dynamics, with the relationship less strong for political news entropy. Allowing for nonlinearities in the impulse response functions substantially alters their shape, resulting in a deeper contraction but then a strong rebound and overshoot, dovetailing with the discussion of a V-shaped recession during the early parts of the SARS-CoV2 pandemic. While we do not yet have the required data to update our news entropy measure through to the ongoing SARS-CoV2 pandemic of 2020, this represents a time of unprecedented levels of both uncertainty and news concentration, with global news coverage focused almost entirely on one topic. This crisis thus acts a clear illustration of our central concept. In future work we plan to document the evolution of news entropy during the pandemic, and to examine the macroeconomic and financial ramifications this had.

Our measure currently only exists for the United States, but a key benefit of our method is how effectively it generalises to news media in other countries, potentially written in other languages. We therefore intend to create news entropy measures for a range of countries, which would allow us to assess whether the impact of news entropy varies internationally.

Lastly, from a methodological perspective, we provide a new, flexible framework that builds on the combination of probabilistic machine learning techniques and information-theoretic concepts. This approach can be adapted to a variety of other probabilistic models to construct economic measures from unstructured data sources in a theoretically well-defined manner.

Appendix A Additional Figures

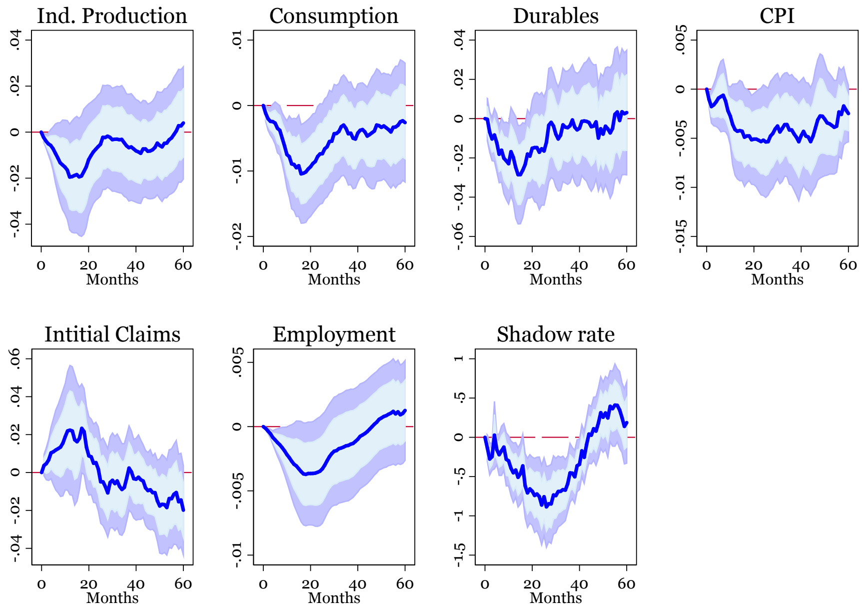


Figure A.1. Responses to News Entropy Indicator Shock.

Note: The light blue shaded area represents the 68% Newey-West adjusted confidence intervals. The dark blue shaded area represents the 90% Newey-West adjusted confidence intervals.

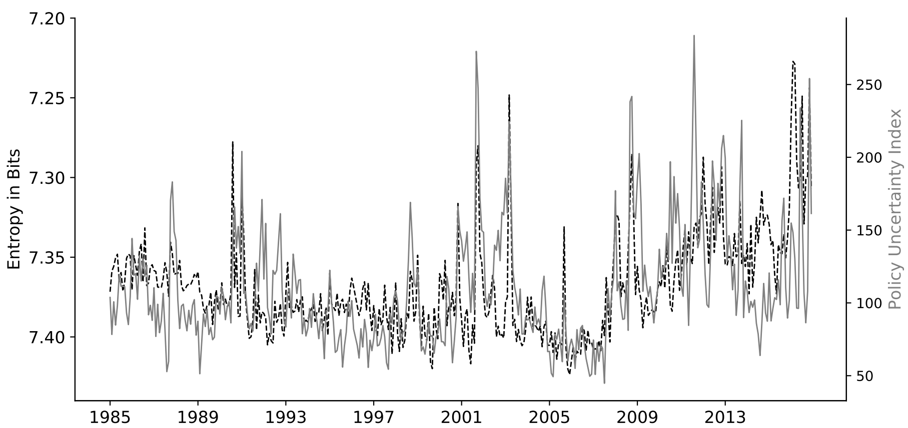


Figure A.2. News Entropy and Policy Uncertainty.

Note: This figure shows our measure and the Policy Uncertainty Index from 1985 to 2016. The ordinate for the news entropy has been inverted to allow for an easier visual comparison.

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