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Indirect news coverage and economic policy uncertainty

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Abstract

This paper uses semantic fingerprints of news to measure news intensity for countries. Estimation results from DCC-GARCH models show that correlations between news intensity and economic uncertainty are mostly positive throughout time. The more relevant news about a country are published, the higher is the economic uncertainty in that country. News intensity also has a negative impact on correlations between uncertainty and inflation, and a positive impact on correlations between uncertainty and output growth.

Keywords: Textual analysis, Semantic fingerprint, Uncertainty

JEL Classification: D8, C3, C8

1. Introduction

News coverage has played an important role in research on the dynamics of financial markets and economic uncertainty. Baker et al. (2016) developed a wide-used index on economic policy uncertainty (EPU) based on the frequency of news articles that contain terms such as economy, uncertainty, etc. There is also a rapidly growing number of studies analysing the impact of information flows via textual analysis in asset pricing (Tetlock, 2014). One natural language processing technology, used to extract information in news articles, is semantic fingerprinting implemented by Cortical.io (Webber, 2015). It projects any text onto a binary vector representing its meaning. Measures for indirect news coverage of an asset based on semantic fingerprinting are used for commodities (Avioz et al., 2023) and currencies (Avioz et al., 2024). The greater the overlap between semantic

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fingerprinting of a news article and an asset, the more relevant that article would be, regardless of whether the asset being mentioned in the news or not. Aggregating this information for considered news articles in a given period provides a measure of news intensity for the relevant asset.

This paper uses this concept of news intensity for countries (instead of assets) and investigates its relation to economic uncertainty in the US and the UK. DCC-GARCH models are adopted to estimate the time-varying correlations. We find correlations between news intensity and economic uncertainty are mostly positive. The more relevant news about a country is published, the higher the economic uncertainty in that country. A higher variance in news intensity is also linked to a higher economic uncertainty. Moreover, news intensity has a negative impact on correlations between uncertainty and inflation, and a positive impact on correlations between uncertainty and output growth in both countries. It can explain about 24% variations in correlations between uncertainty and inflation in the US.

2. Data and Methodology

EPU data for the US and the UK are obtained from the website of the Economic Policy Uncertainty Index. For the news intensity measure, we consider online articles from the New York Times published between January 1998 and May 2023. Following Avioz et al. (2023), let $N(t)$ be the total number of news stories on day t. Corresponding to each news story is a semantic fingerprint comprising a subset of K possible positions, each of them representing a group of related terms. We define I as a K-vector containing the semantic fingerprint of a country, and $J_{n,t}$ as a K-vector containing the semantic fingerprint of the nth news story on day t. The news intensity score for this country on day t is defined as the average of the number of news stories whose fingerprints include a given position, taken across all positions comprising the country's fingerprint, and scaled by the average number of stories across all possible positions:

$$ni_t = \frac{(\Sigma_{n=1}^{N(t)} I \cdot J_{n,t})/ \parallel I \parallel}{(\Sigma_{n=1}^{N(t)} \parallel J_{n,t} \parallel)/K}.$$

The higher the news intensity score, the more relevant news about a country is published[1].

We use the dynamic conditional correlation (DCC)-GARCH model (Engle, 2002), to investigate the time-varying relationship between economic uncertainty and news intensity, and then the impact of the news intensity on the time-varying relationship between economic uncertainty and macroeconomic variables.

Let $y_t = (y_{1t}, y_{2t})'$ be a vector of two variables. The conditional mean equation for y_t is a VAR model. The conditional variance-covariance matrix $H_t = D_t R_t D_t$ for the residuals (ϵ_t) in the mean equation is decomposed into products of the diagonal matrix $D_t = diag\{\sqrt{h_{it}}\}$ for $i = 1, 2$, with the time-varying standard deviations on the diagonal, and the correlation matrix $R_t = \{\rho_{ij}\}_t$ for $i, j = 1, 2$, containing the time-varying conditional correlation coefficients in the off-diagonal elements. The standard deviations are then modelled as the GARCH(1,1) process,

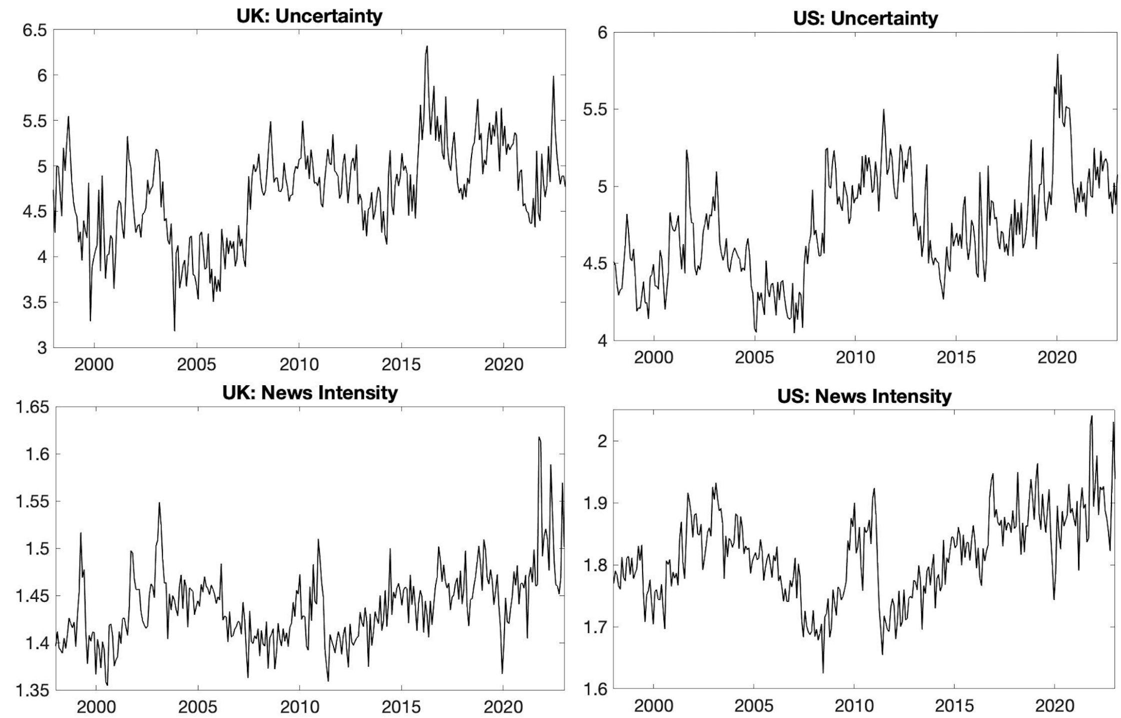
$$h_{it} = \gamma_i + \alpha_{i1}\epsilon_{i,t-1}^2 + \beta_{i1} h_{i,t-1}.$$

The correlation matrix follows DCC(1,1) structure, with $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, where

$$Q_t = (1 - a - b)\overline{Q} + a\epsilon_{t-1}^2 + bQ_{t-1}.$$

$\overline{Q}$ is the unconditional covariance matrix of ϵ_t and Q_t^* is the diagonal matrix containing the square root of the diagonal elements of Q_t.

Figure 1: Economic uncertainty index and news intensity



3. Results

Figure 1 illustrates EPU in logarithm (u_t) and news intensity (ni_t). These two series share some common patterns, particularly visible for the US. Stationarity of the two series can be confirmed via usual unit root tests. Table 1 reports the results from the DCC-GARCH models. We find significant lagged impacts from news intensity on uncertainty or vice versa (see Panel A). For the mean equation, we also consider the conditional variance of both variables (hu_t and hni_t). A higher variance in news intensity is linked to a higher economic uncertainty for both countries. The DCC-GARCH methods are supported by the data (see Panel B). ARCH coefficients (α) are significant for both countries and GARCH coefficients (β) are significant for the UK. The estimated correlations between uncertainty and news intensity have significant and large AR(1) coefficients (b). The number of lags in the mean equation is chosen so that no autocorrelations at the low lags can be found

[1]Monthly measures of news intensity are obtained as the average daily measures of the month.

in the residuals (see Panel C).

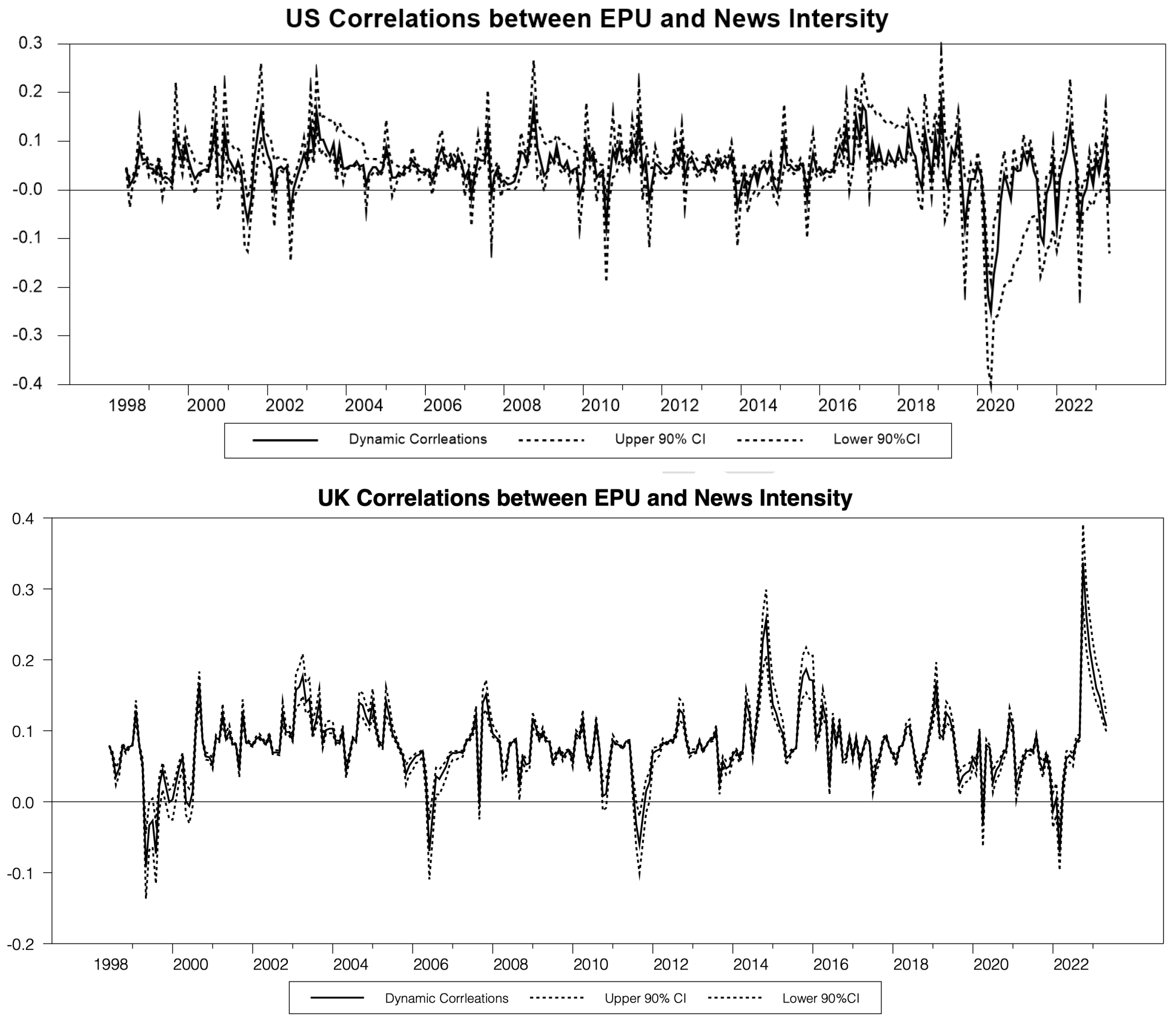
Table 1: Birvariate DCC-GARCH models for Uncertainty and News Intensity

Panel A: Mean estimates:				
	US		UK	
	u_t	ni_t	u_t	ni_t
Constant	0.910 ***	0.114**	0.799***	0.260***
ni_{t-1}	-0.459***	0.500***	0.700***	0.550***
ni_{t-2}	0.171	0.113***	-1.536***	0.025***
ni_{t-3}	0.310*	0.246***	-0.216***	0.209***
ni_{t-4}	-0.145	0.097**	1.579***	-0.029***
ni_{t-5}	-0.104	-0.062**	-0.882***	0.056***
u_{t-1}	0.594***	-0.007	0.579***	0.005***
u_{t-2}	0.091***	0.029***	0.130***	-0.002***
u_{t-3}	-0.030	0.001	0.104***	-0.002***
u_{t-4}	0.109*	-0.033***	0.042***	-0.004***
u_{t-4}	0.125***	0.022***	0.024***	0.006***
hu_t	-1.480	3.098	0.768***	-8.624***
hni_t	50.581***	0.632*	301.154***	-0.010
Panel B: Conditional variance estimates:				
	US		UK	
	hu_t	hni_t	hu_t	hni_t
γ	0.023***	0.001***	0.071***	0.000***
α	0.179*	0.322***	0.288***	0.046***
β	-0.007	0.154	-0.164***	0.580***
a	0.030		0.047	
b	0.889***		0.736***	
Panel C: Ljung-Box Q-statistics (Standardized residuals):				
	US		UK	
	Uncertainty	News intensity	Uncertainty	News intensity
4	1.392	2.742	0.397	0.190
8	2.452	6.075	2.085	0.860

Note: Significance at 1%, 5%, and 10% is indicated with ***, **, and * accordingly.

The estimated correlations between economic uncertainty and news intensity are positive and significantly different from zero for most of the time (see Figure 2). For the UK, it is around 0.1 on average, and fluctuates mostly between 0.2 and 0. For the US, the average correlation is around 0.05, and varies mostly between 0.1 and 0.

Figure 2: Correlations between uncertainty and news intenesity



The correlations between macroeconomic uncertainty and inflation/output can vary through time (Jones and Olson, 2013). To investigate the impact of news intensity on the relationship between uncertainty and macroeconomic variables, we first estimate the time-varying correlations between uncertainty (u_t) and inflation (π_t), and between uncertainty (u_t) and output growth (y_t) via DCC-GARCH models. The inflation (output growth) is measured as log monthly changes in CPI (industrial production) multiplied by 1200[2].

[2]Note the CPI index of the UK from Fred is adjusted seasonally using X-11 approach.

In addition to the conditional variance of the considered series (hu_t, $h\pi_t$ and hy_t), we also add dummy variables taking into account the impact of the financial crisis (D_F) and Coronavirus diseases (D_{COV}) on inflation and output in the mean equation [3]. We find a higher variance in uncertainty is linked to a higher US inflation and output (see Panel A). The financial crisis and COVID have significant impacts on inflation and output growth. Also, the DCC-GARCH method is supported by the data (see significant ARCH and GARCH coefficients as well as the AR(1) coefficient in correlations in Panel B).

The estimated correlations between uncertainty and inflation are more persistent than those between uncertainty and output growth (see Figure 3). Correlations between uncertainty and inflation in the US decreased slowly from positive to negative around late 2012, while those in the UK remained positive for most of the time. When we regress these correlations on news intensity, we find news intensity has a negative impact on correlations between uncertainty and inflation, but a positive impact on correlations between uncertainty and output (see Table 3). This evidence is robust across both countries. The coefficients for news intensity are significant at 1% level. Also, news intensity can explain about 24% variations in correlations between uncertainty and inflation in the US.

4. Conclusion

This paper uses semantic fingerprints of New York Times articles to construct measures of news intensity for the US and the UK. We find that a higher level or variance in news intensity is linked to a higher economic uncertainty. Also, news intensity impacts the correlation between uncertainty and inflation negatively, and the correlation between uncertainty and output growth positively.

The identified positive correlation between news intensity and economic uncertainty

[3] The dummy variable D_F is set to one for August–December 2008 when modelling uncertainty and inflation in the US, and for August–September 2008 when modelling uncertainty and output in the US. The dummy variable D_{COV} is set to one for March–April 2020 when modelling uncertainty and output in the US, for July 2021 – May 2023 when modelling uncertainty and inflation in the UK, and for March - May 2020 when modelling uncertainty and output in the UK. Although unit root tests confirmed the stationarity of all used series without introducing any dummy variable, we find using these dummy variables helps to mitigate the impact of outliers and potential structure breaks on model estimates.

Table 2: Birvariate DCC-GARCH model for Uncertainty, Inflation and Output

Panel A: Mean estimates:								
	US				UK			
	Uncertainty/Inflation		Uncertainty/output		Uncertainty/Inflation		Uncertainty/output	
	u_t	π_t	u_t	y_t	u_t	π_t	u_t	y_t
Constant	0.407***	0.974***	0.514***	-2.115	0.639***	1.273	0.546***	-4.309**
π_{t-1}	-0.005**	0.530***		0.086	-0.002	0.104*		
π_{t-2}	0.004	-0.221***		0.135**	0.005	0.122**		
π_{t-3}	-0.001	-0.005		0.110**				
π_{t-4}	0.004*	0.008		0.168***				
u_{t-1}	0.662***	-2.756***	0.642***	0.191	0.656***	0.186	0.666***	2.621***
u_{t-2}	0.081***	2.93***	0.098	-5.102**	0.221***	-0.028	0.068***	-5.115***
u_{t-3}	-0.0001	0.247***	-0.054	-0.527			0.132***	3.390***
u_{t-4}	0.176***	-0.333***	0.213***	5.826***				
y_{t-1}			-0.001**				0.001***	-0.093*
y_{t-2}			0.001*				0.0002	0.030
y_{t-3}			-0.001**				-0.0001	0.086*
y_{t-4}			0.001*					
hu_t	-0.462	0.080***	-1.324	0.021***	-0.774	-0.068	0.889***	0.004
$h\pi_t$	-0.0004	-20.076**			-0.002	-3.095		
hy_t			0.0001	-1.026			-0.00003**	-3.599
D_F	0.095**	-8.686***	0.206***	-29.639***				
D_{COV}			0.426***	-81.264***	0.077	6.501***	0.381***	-118.896***
Panel B: Conditional variance estimates:								
	US				UK			
	Uncertainty/Inflation		Uncertainty/output		Uncertainty/Inflation		Uncertainty/output	
	hu_t	$h\pi_t$	hu_t	hy_t	hu_t	$h\pi_t$	hu_t	hy_t
γ	0.015***	1.326***	0.015*	8.640***	0.024	0.168	0.080***	79.700***
α	0.257***	0.121***	0.190**	0.401***	0.217**	0.141***	0.261***	0.631***
β	0.244*	0.781***	0.279	0.539***	0.526*	0.838***	-0.166***	0.122***
a	0.025*		0.047		0.027		0.128**	
b	0.961***		0.912***		0.928***		0.724***	
Panel C: Ljung-Box Q-statistics (with standardized residuals)								
	US				UK			
	Uncertainty/Inflation		Uncertainty/output		Uncertainty/Inflation		Uncertainty/output	
	Uncertainty	Inflation	Uncertainty	output	Uncertainty	Inflation	Uncertainty	output
4	3.011	1.012	4.707	9.099	4.581	1.957	1.189	4.262
8	4.894	2.825	7.415	12.142	7.576	8.968	3.601	8.276

Note: Significance at 1%, 5%, and 10% is indicated with ***, **, and * accordingly.

Figure 3: Correlations

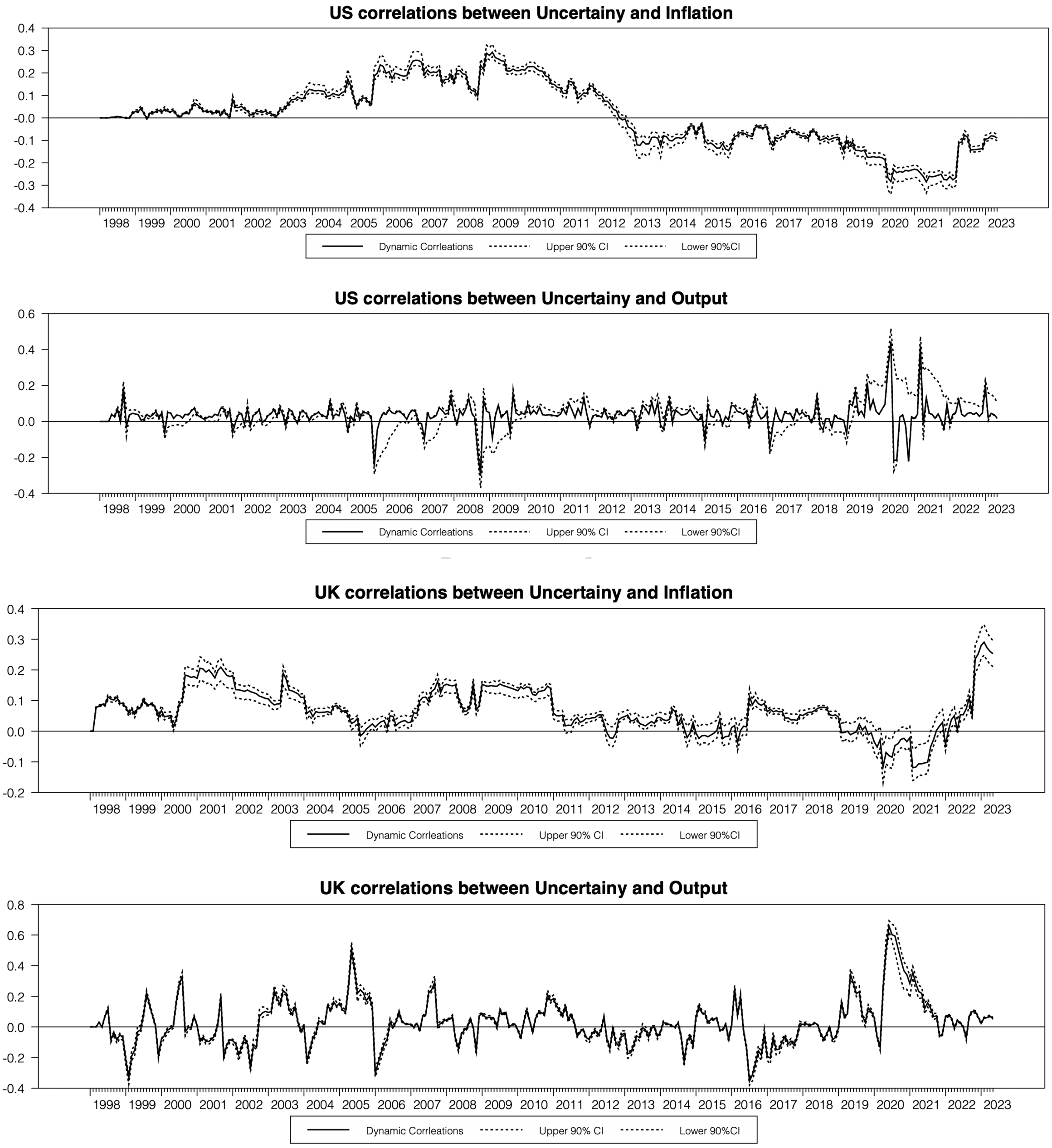


Table 3: OLS regression of time-varying correlations on news intensity

	US		UK	
	$\rho(u_t, \pi_t)$	$\rho(u_t, y_t)$	$\rho(u_t, \pi_t)$	$\rho(u_t, y_t)$
constant	1.745***	-0.640***	0.470***	-1.123***
ni_t	-0.956***	0.377***	-0.281***	0.797***
R^2	0.242	0.051	0.019	0.034

Note: Significance at 1%, 5%, and 10% is indicated with ***, **, and * accordingly.

promotes future research into identifying and explaining causal links between them theoretically and empirically. On the one hand, news coverage itself is a signal that can increase uncertainty (Nimark, 2014). On the other hand, unusual economic events of a country might draw interest of the public, and thus encourage more general news coverage of that country. Therefore, we speculate there can be bidirectional causality among the two series.

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Data Availability

The news intensity data underpinning this publication can be accessed from Brunelfigshare: `https://doi.org/10.17633/rd.brunel.27854760`. The EPU data is obtained from `https://www.policyuncertainty.com`. CPI and industrial production data are downloaded from `https://fred.stlouisfed.org`.

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