Analysing News Media to Form Expectations on the Uncertain Future: the Issue of Endogeneity

Article · June 2015

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Analysing News Media to Form Expectations on the Uncertain Future: the Issue of Endogeneity

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June 2015

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We are grateful to David Tuckett of UCL for discussions on this topic. We also wish to thank Chrystia Freeland, Richard Brown and Maciej Pomalecki of Thomson Reuters for arranging access to the Reuters News archive

Abstract

The analysis of news media or other digital sources to derive systematic information about future expectations and behaviour is a promising recent development within applied economics. Advances in computer science and technology now enable even very large text data bases to be searched speedily and efficiently. However, as in the early days of applied econometrics, much remains to be discovered about appropriate methodologies. This paper addresses the issue of the potential endogenous nature of information obtained by this kind of analysis. We contrast a time series which measures economic policy uncertainty, and which uses explicit economic terms in its construction, with two other series, which do not. One of these is particularly simple, being a count of the number of times the words 'uncertain' and 'uncertainty' appear in Thomson-Reuters news feeds. The other has an explicit theoretical foundation based upon agent decision making under Knightian uncertainty. Over the 1996-2014 period for the United States, we find that the latter two Granger cause the former, at both the monthly and quarterly data frequencies. They also Granger cause both quarterly real GDP and the Anxious Index of the Society of Professional Forecasters, which the economic policy uncertainty series does not. These results suggest potential problems in using explicit economic terms and concepts in algorithmic text analysis in the context of future expectations. Any data series derived in this way may be endogenous to the economy and hence lack explanatory power about the future. The overall performance of the theoretically based measure is distinctly superior, overall, to the two atheoretical measures, suggesting another dimension which may be of importance in text analysis in economics.

Keywords: expectations; uncertainty; text analysis; endogeneity

JEL classification: B40; C55; D84

1. Introduction

The analysis of news media or other digital sources to derive systematic information about future expectations and behaviour is a recent phenomenon within economics, with most of the literature being a feature of the most recent past five years (for example, Ramey and Shapiro, 1999; Romer and Romer, 2010; Dominguez and Shapiro, 2013; Baker et al., 2013, 2014; Choi and Varian, 2012; Haddow et al 2013, Tuckett et al. 2014, Monet 2014, Tuckett et al. 2015, Nyman et al. 2015).

The approach shows considerable promise. However, as is the case with any new development such as this, important methodological issues remain to be settled. We might usefully think, for example, of the development of econometrics, both cross-section and time series, over the decades since the Second World War. Enormous progress has been made in methodology over this time scale, but at the outset, much remained to be discovered about analytical methods. Even a cursory reading of the pioneering macro-econometric models of Klein, for example, in the late 1940s makes this apparent (Klein 1947)

It is obviously not possible to resolve methodological issues around the analysis of media to form expectations in a single article. But the longest march begins with a single step. In this short paper, we address the question of the extent to which the analysis of media in the context of expectation formation should include explicitly economic concepts and information, and the extent to which the focus should be on information which is orthogonal to these features.

Baker et al. (2013) develop an index of economic policy uncertainty (EPU) based on a range of indicators which contain a great deal of economic content. There are three aspects of economic policy uncertainty which make up the index: (i) the frequency of references to policy related economic uncertainty in 10 leading U.S. newspapers; (ii) the number and revenue impact of federal tax code provisions set to expire in future years; and (iii) the extent of disagreement among economic forecasters over future government purchases and future inflation.

In this note, we compare the EPU with a very simple index constructed from an algorithmic count of the words 'uncertain' and 'uncertainty' in the Thompson-Reuters news feeds over the 1996 – 2014 period. We denote this for descriptive purposes as UNCERT. We extend the comparison to the 'relative sentiment shift' (RSS) measure described by Tuckett et al. (2015). This is also based on algorithmic word counts in the Thompson-Reuters news feeds.

In the RSS case, the search is directed by a theoretical model of agent behaviour under uncertainty (Tuckett and Nikolic 2015) to count specific words in two separate lists. Within one list, the words represent the emotion of excitement about gain, and in the other, the emotion of anxiety about loss. The RSS in any given period is the difference between the total number of words which appears in the news feed from each list, normalised by the total number of documents in the news feed. The words are validated in psychological experiments to ensure that they represent the relevant emotions. Crucially, the words are words which are in everyday use in English, and have no particular economic meaning.

These three series, EPU, UNCERT and RSS are available on a monthly basis, and we first of all carry out Granger causality tests between them using this data frequency. Many macroeconomic series are only available quarterly, so we also carry out causality tests between them when the series are put onto a quarterly basis. We extend the set of variables in the Granger tests to include quarterly real GDP growth in the United States, and also the Anxious Index published by the Philadelphia Fed, and which is based on a survey of professional forecasters and which gives the probability of a decline in real GDP in the quarter after the survey is carried out**.** We then examine the extent which each of the three series adds significant explanatory power to a regression of quarterly real GDP growth on the Survey of Professional Forecasters' consensus prediction made in the previous quarter.

Section 2 describes the data in more detail, section 3 sets out the results, and section 4 offers a short discussion.

2. The data

As noted above, there are three aspects of economic policy uncertainty which make up the EPU index: (i) the frequency of references to policy related economic uncertainty in 10 leading U.S. newspapers; (ii) the number and revenue impact of federal tax code provisions set to expire in future years; and (iii) the extent of disagreement among economic forecasters over future government purchases and future inflation.

The news-based component of the index reflects automated text searches of 10 leading newspapers in the US. identify articles containing 'uncertainty' or 'uncertain', 'economic' or 'economy', and one or more of the following terms: 'congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation' or 'white house' (including related terms like 'regulatory' or 'the Fed').7 In other words, to meet the criteria, the article must include terms in all three categories pertaining to uncertainty, the economy, and policy. A monthly article count is obtained for each newspaper, and the raw count is normalised by the total number of articles in the same newspaper and month. Baker et al. (op. cit.) describe how they construct the overall index by combining this with the information in tax code provisions

and disagreement among economic forecasts. The key point for this paper is that even the news-based component requires explicit economic terms to appear in order for an article to be counted. The specific source of the EPU index is http://www.policyuncertainty.com/us_monthly.html.

We were given access to the Thomson- Reuters News archive of articles published each day between 1996 and 2014. Reuters provide extensive documentation and for this paper we select only articles with RTRS (Reuters) as the attribution, English as the language, published in the New York or Washington offices, and so defined as US focused. Articles with the tags SPO (sports), ODD (human interest) or WEA (weather) were removed. This leaves a total of some 2.2 million articles over the 1996-2014 period.

We constructed a very simple index of uncertainty based on an algorithmic count of the number of times the words 'uncertain' and 'uncertainty' appear in the news archive. The raw count was divided by the total number of articles. We denote this simple atheoretical series by 'UNCERT'.

The RSS series (Tuckett et al. 2014, 2015) is based upon a theoretical model of decision making under uncertainty known as conviction narrative theory (Tuckett 2011, Tuckett and Nikolic op.cit.). In this approach, expectations are conceived as being created by the capacity of human agents to simulate and communicate mental pictures of future outcomes that they *feel* are accurate. Under uncertainty, agents need to balance two emotions in order to make decisions at all rather than being paralysed into inaction. These emotions are excitement about gain and anxiety about loss.

Psychological experiments are carried out to obtain lists of some 150-200 words each which convey the emotions of excitement about gain and anxiety about loss. They are words in everyday use in English, such as 'jitter' and 'fears' which convey anxiety, and 'enjoy' and 'brilliant', which convey excitement. An algorithmic search of the Reuters news archive, with the same coverage as that used for UNCERT, is carried out each day, and a raw count is obtained of the sum of the words measured by each of the emotions. The anxiety count is subtracted from the excitement count, and this net figure is divided by the total number of articles searched in order to obtain the daily RSS series. Both this and the UNCERT series are converted to either a monthly or a quarterly basis by averaging the daily values of RSS within the relevant month of quarter.

The key contrast between the EPU series and both the UNCERT and RSS series is that the former contains content which is specific to the economy and the latter two do not.

There is in addition a key distinction between the EPU and UNCERT series, and the RSS series. The words which are used in the construction of the first two are essentially ad hoc.

This does not mean that care was not used the selection of the words underlying the EPU series, but that the list represents a judgement about the sorts of words which seemed relevant to uncertainty and the economy. In contrast, the words used to generate the RSS series are specifically chosen on the basis of a theory of agent behaviour under uncertainty. The search is in this case directed by the theoretical model of micro-level behaviour.

3. Results

3.1 The data and simple correlations

The series move closely together over the January 1996 – September 2014 period. Table 1 shows the simple correlations between them, with the sign on the RSS variable is changed so that it moves in the same direction as the other two variables. An increase in the raw RSS data means that excitement is rising relative to anxiety, a positive feature, so we switch this to make it comparable in direction. An increase in either EPU or UNCERT means that uncertainty is rising.

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Table 1: Simple correlations between EPU, UNCERT and RSS, January 1996 – September 2014

Variable	EPU	RSS	UNCERT
EPU	1	0.786	0.779
RSS	-	1	0.791
UNCERT	-	-	1

3.2 Granger causality tests of the data on a monthly basis

We investigated the directions of Granger causality between the three variables, EPU, UNCERT and RSS.

We use the methodology described in Toda and Yamamoto (1995). In outline, in investigating Granger causality between any two series, this is as follows:

1. Check the order of integration of the two series using Augmented Dickey-Fuller (Said and Dickey 1984; p-values are interpolated from Table 4.2, p. 103 of Banerjee et al.

1993) and the Kwiatowski-Phillips-Schmidt-Shin (1992) tests. Let *m* be the maximum order of integration found.

2. Specify the VAR model using the data in levelled form, regardless of what was found in step 1, to determine the number of lags to use with standard method. We use the Akaike Information Criteria
3. Check the stability of the VAR (we use OLS-CUSUM plots, which are reported in the Supplement).
4. Test for autocorrelation of residuals. If autocorrelation is found, increase the number of lags until it goes away. We use the multivariate Portmanteau- and Breusch-Godfrey tests for serially correlated errors. Let p be the number of lags then used.
5. Add m extra lags of each variable to the VAR.
6. Perform Wald tests with null being that the first p lags of the independent variable have coefficients equal to 0. If this is rejected, we have evidence of Granger-causality from the independent to dependent variable.

We used the statistical program R to carry out the analysis, and the various packages used to carry out the above Toda-Yamamoto procedure are documented in the Supplement.

We discuss the results of steps 1 – 4 (and 5 when required) in the Supplementary Material, and focus in the main text on step 6 only, namely the specific tests of Granger causality. These are set out in Table 2 below.

Table 2 Wald test statistics of Granger-causality between EPU and UNCERT; EPU and RSS; UNCERT and RSS, monthly data, January 1996 – September 2014

Direction	Chi-Sq	d.f.	p-value
EPU-> UNCERT	2.4	5	0.80
UNCERT -> EPU	18.8	5	0.002***
RSS -> EPU	31.1	8	0.0001***
EPU -> RSS	8.9	8	0.35
RSS -> UNCERT	13.1	4	0.011**
UNCERT -> RSS	21.1	4	3e-04***

Note: *p<0.1; **p<0.05; ***p<0.01

The results indicate that Granger causality using monthly data runs from the RSS and UNCERT variables to EPU and not vice versa. There is causality in both directions between RSS and UNCERT.

3.3 Granger causality tests of the data on a quarterly basis

We convert the series from monthly to quarterly by averaging the results within each quarter. We extend the causality tests to include DLGDP, the quarterly growth of real GDP in the US[1], and ANX, the Anxious Index published by the Philadelphia Fed, and which is based on a survey of professional forecasters and which gives the probability of a decline in real GDP in the quarter after the survey is carried out[2].

The results of the Granger causality tests are set out in Table 3 below, and, again, the preceding steps in the test procedure are documented in the Supplementary Material.

Table 3 Wald test statistics of Granger-causality, quarterly data, 1996Q1 – 2014Q3

Direction	Chi-Sq	d.f.	p-value
EPU -> UNCERT	0.15	2	0.93
UNCERT -> EPU	2.2	2	0.34
EPU-> RSS	1.6	2	0.45
RSS -> EPU	19.2	2	7e-05***
RSS-> UNCERT	9.3	1	0.002***
UNCERT -> RSS	1.1	1	0.29
EPU -> GDP	1.2	1	0.27
GDP -> EPU	0.58	1	0.44
UNCERT -> GDP	3.4	1	0.07*
GDP -> UNCERT	0.28	1	0.60
RSS -> GDP	3.7	1	0.055*
GDP -> RSS	0.04	1	0.85
ANX -> EPU	0.48	2	0.79
EPU -> ANX	3.6	2	0.16
ANX -> RSS	2.1	2	0.34
RSS -> ANX	20.3	2	4e-05***
ANX -> UNCERT	0.35	2	0.84
UNCERT -> ANX	6.7	2	0.035**

Note: *p<0.1; **p<0.05; ***p<0.01

Using data at the quarterly frequency, the direction of causality runs from RSS to EPU and UNCERT and not vice versa. But the strong causal relationships observed from UNCERT in the higher frequency monthly data disappears at the lower frequency.

In terms of causal relationships between quarterly real GDP growth and these variables, there is evidence of causality from both RSS and UNCERT to GDP, but not from EPU. The

[1] Obtained from Table 1.1.6 of the National Income and Product Accounts at www.bea.gov

[2] http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index/

same point obtains in the relationships between the Anxious Index and the three variables, although causality here, where it exists, is much more strongly determined.

3.4 Professional forecasts

The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. A discussion of the historical accuracy of the forecasts, for both GDP and other economic variables, is given in Stark (2010).

It is well known that the raw output of whatever model is being used is rarely published as the actual forecast. Professional forecasters exercise judgement, often considerable, in shaping the forecast which is published. An early illustration of this is Surrey and Ormerod (1977). The UK's Office for Budget Responsibility (OBR), an independent body which is tasked by Parliament to produce the economics forecasts used by the government, stresses the role of judgement, stating (2011): "The most important parts of any forecast are the judgements that underpin it" (p.8).

The question is therefore whether the information contained in the various emotion measures considered here is additional to the judgement exercised by professional forecasters in making their predictions. If the variables (EPU, RSS and UNCERT) do not add to the explanatory power of a regression of the growth in actual GDP over what was predicted, we might reasonably conclude either that the additional series contains no worthwhile information, or that professional forecasters were aware of it and used it in the process of adjusting the raw output of their forecasting models.

The consensus forecasts over time are unbiased. However, they are able to account for only a relatively small fraction of the overall variance in quarterly real GDP growth. We confirm this finding in the literature by regressing quarterly real GDP growth in quarter *t* on the consensus forecast for quarter *t* made in quarter *t-1* over the period 1996Q1 through 2014Q3.

Table 4 Regression of the actual values of quarterly growth in real US GDP (DLGDP) on the consensus forecast made in the previous quarter (SPF); on SPF and EPU; on SPF and UNCERT; on SPF and RSS, 1996Q2-2014Q3

SPF	1.124***	0.962***	0.985***	0.829***	0.901***
	(0.292)	(0.320)	(0.300)	(0.304)	(0.315)
EPU		-0.011			0.019
		(0.009)			(0.016)
UNCERT			-0.504*		0.092
			(0.294)		(0.551)
RSS				0.765**	1.388**
				(0.299)	(0.599)
Constant	-0.430	1.154	-0.072	0.325	-1.947
	(0.804)	(1.526)	(0.820)	(0.829)	(2.062)
R^2	0.170	0.187	0.203	0.240	0.261
Adjusted R^2	0.159	0.164	0.181	0.219	0.218
Residual Std. Error	2.469	2.461	2.437	2.379	2.380

Note: *p<0.1; **p<0.05; ***p<0.01

In the regression of GDP growth on the forecast variable alone, SPF, the constant term is not significantly different from zero and the coefficient on the explanatory variable is not significantly different from one, although the overall explanatory power is very low. These results obtain when each of the three variables, EPU, UNCERT and RSS is added separately to the regression.

However, when EPU is added, the explanatory power of the equation is not improved. The coefficient on the UNCERT variable, when also added separately, is significantly different from zero at a p-value of 0.091. The RSS variable is a more powerful explanator, with its coefficient being significantly different from zero at a p-value of 0.013. In the regression in

which all three emotion variables are included, along with the SPF variable, the p-value of the null hypothesis that the estimated coefficient on the explanatory variable is significantly different from zero rejected at 0.023 for RSS, and at 0.223 for EPU and 0.867 for UNCERT respectively.

4. Discussion and conclusion

The striking feature of the results overall is that the EPU series is effectively dominated by both RSS and UNCERT, the former in particular. In tests of Granger causality between each pair of these three variables, using both monthly and quarterly data, causality in general runs from RSS and UNCERT to EPU rather than from EPU. Further, causation runs from RSS and UNCERT to both GDP and the Anxious Index, with no evidence that EPU causes these latter variables in the sense of Granger.

In addition, the RSS variable adds significant explanatory power to a regression of actual real quarterly GDP growth on the prediction in the previous quarter given by the consensus of the Society of Professional Forecasters, whereas again the EPU variable does not.

The EPU series is constructed by amalgamating several types of information, all of which incorporate explicit economic information. The news-based component of the index, for example, requires specific economic terms to appear in a news article for it to be counted towards the measure of the index.

The UNCERT variable goes to the other extreme. It is a simple count (obtained algorithmically for accuracy) of the number of times the words ‘uncertain’ and ‘uncertainty’ appear in the Thomson-Reuters newsfeeds. This is the only information which is used to construct the series, yet it Granger causes movements in the EPU series, and is also causal in this sense with respect to quarterly GDP growth and the Anxious Index.

The RSS series is considerably more sophisticated than the UNCERT series. It is based on explicit micro-foundations of a social-psychological theory of how agents make decisions under conditions of uncertainty. It, too, is based on word counts in the Thomson-Reuters newsfeeds, but none of the words used has explicit or specialised economic meaning.

There are two reasonable conclusions to draw. First, endogeneity is a potentially serious problem for the promising approach of analysing news media or other digital sources to derive systematic information about future expectations and behaviour. The second conclusion is that the measure used in this paper which has explicit micro theoretic foundations is distinctly superior overall to the two atheoretical measures.

Of course, this short paper cannot be regarded as in any way definitive. It is merely indicative. But it suggests that great care needs to be exercised in such analysis when specific economic terms or concepts are used.

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Appendix

The packages in R used in the Toda-Yamamoto procedure to investigate Granger causality are as follows:

- *tseries* – we use the two functions *adf.test* and *kpss.test* (the Augmented Dickey-Fuller test and Kwiatkowski-Phillips-Schmidt-Shin test respectively) to check if series are stationary or contain unit roots. The *adf.test* function allows you to define the alternative hypothesis by the “alternative” argument. We use the default option of “stationary”. The function also allows you to manually specify the lag order *k* to calculate the test statistic. We use the default option k=trunc((*N*-1)^(1/3)), where *N* is the length of the series and *trunc* is a function built into R truncating the value towards zero
- *vars* – we use the function *VARselect* to compute the Akaike Information Criteria for VAR(p) processes with p from 1 through 20. The function takes a number of arguments. We make use of the “lag.max” argument, which we set to 15 and the “type” argument which we set to “const”, indicating that information criteria should be computed for lags from 1 through 15 and that a constant term should be included in the VAR, respectively. We use the *VAR* function for estimating a VAR(p) process. Similarly to *VARselect* we use the “p” argument specifying the number of lags to include and the “type” argument specifying whether to include a constant term, or a trend or both. In all cases we set this argument to “const”, indicating that only a constant term should be included. We use the function *serial.test* to compute the multivariate Portmanteau- and Breusch-Godfrey tests for serially correlated errors in a VAR(p) process. We use the default number of lags for each test. In the case of the Portmanteau test we keep the default value of the “lags.pt” argument at 16 and in the case of the Breusch-Godfrey test we keep the default value of the “lags.bg” argument at 5. We set the “type” parameter to either “PT.asymptotic” or “BG” to compute the Portmanteau- or Breusch-Godfrey test respectively. We use the function *stability* to

compute empirical fluctuation processes according to the OLS-CUSUM method. We use the default values of each argument, in particular the "type" argument which defaults to "OLS-CUSUM" for the OLS-CUSUM method. The figures for the empirical fluctuation processes are generated by the use of the built in *plot* function on the returned object from the call to *stability*

- *aod* – we use the function *wald.test* to perform the Wald tests for Granger causality. We use three of the function's available arguments. The argument "Terms" specifying which terms of the model to include in the null hypothesis of the Wald test, given as a vector of term indices. The argument "b" specifying a vector of the coefficients of the model. The argument "Sigma" specifying the variance-covariance matrix of the model. To specify the values of the latter two arguments, we use the *coef* method on the relevant equation from the VAR to extract the relevant coefficients and the *vcov* method on the relevant equation from the VAR to extract the relevant variance-covariance matrix

Table A1

Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests for stationarity of monthly series

Variable	ADF (lag)	p-value	KPSS (lag)	p-value
EPU Level	-2.49(6)	0.37	2.21 (3)	< 0.01***
EPU Diff	-7.78 (6)	< 0.01***	0.04 (3)	> 0.1
UNCERT Level	-3.20 (6)	0.09*	1.09 (3)	<0.01***
UNCERT Diff	-7.10 (6)	<0.01***	0.02 (3)	> 0.1
RSS Level	-2.91 (6)	0.19	2.32 (3)	< 0.01***
RSS Diff	-6.93 (6)	< 0.01***	0.03 (3)	> 0.1

Notes: 1. *p<0.1; **p<0.05; ***p<0.01

2. the figures in brackets in the ADF and KPSS columns indicate the lag order and the truncation lag parameter respectively

The analysis implies that all variables should be treated as integrated of order 1.

Table A2

Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests for stationarity of quarterly series

Variable	ADF (lag)	p-value	KPSS (lag)	p-value
EPU Level	-1.55 (4)	0.76	1.56 (1)	< 0.01***
EPU Diff	-3.57 (4)	0.04**	0.09 (1)	> 0.1
UNCERT Level	-2.09 (4)	0.54	0.80 (1)	< 0.1
UNCERT Diff	-4.36 (4)	<0.01***	0.04 (1)	> 0.1
RSS Level	-2.31 (4)	0.45	1.63 (1)	< 0.01***
RSS Diff	-4.10 (4)	< 0.01***	0.05(1)	> 0.1
GDP Level	-2.79 (4)	0.25	0.78 (1)	<0.01***
GDP Diff	-5.04(4)	<0.01***	0.03 (1)	> 0.1
ANX Level	-2.91 (4)	0.21	0.27 (1)	<0.01***
ANX Diff	-3.94 (4)	0.02**	0.03 (1)	> 0.1

Notes: 1. *p<0.1; **p<0.05; ***p<0.01

. 2. the figures in brackets in the ADF and KPSS columns indicate the lag order and the truncation lag parameter respectively

3. GDP is the quarterly growth rate of real GDP

The analysis implies that all variables should be treated as integrated of order 1.

The results of the Akaike Information Criteria for the order of the VAR model in level form, and the results of the investigation of the stability of the preferred VAR using OLS-CUSUM plots are available on request from the authors. The lag order indicated by these tests was on a few occasions modified in order that the VAR models should satisfy the tests for serially correlated errors reported below.

Table A3

Multivariate Portmanteau- and Breusch-Godfrey tests for serially correlated errors of VAR models, monthly data

VAR model	Portmanteau	d.f.	p-value	Breusch-Godfrey	d.f.	p-value
EPU/RSS	44.50	32	0.07*	16.86	20	0.66
EPU/UNCERT	57.77	44	0.08*	18.91	20	0.53
RSS/UNCERT	55.71	48	0.21	14.52	20	0.80

Note: *p<0.1; **p<0.05; ***p<0.01

There is very weak evidence of autocorrelation in the EPU/RSS and EPU/UNCERT VAR models. We experimented with different orders the relevant VAR models either side of the order indicated in each case by the AIC criteria for model selection. However, there was more evidence of autocorrelation in these models.

Table A4

Multivariate Portmanteau- and Breusch-Godfrey tests for serially correlated errors of VAR models, quarterly data

VAR model	Portmanteau	d.f.	p-value	Breusch-Godfrey	d.f.	p-value
EPU/UNCERT	52.26	56	0.62	23.46	20	0.27
EPU/ RSS	45.94	56	0.83	28.00	20	0.11
RSS/UNCERT	62.18	60	0.40	15.89	20	0.72
EPU/GDP	60.38	60	0.46	20.78	20	0.41
UNCERT /GDP	67.63	60	0.23	26.15	20	0.16
RSS /GDP	42.15	60	0.96	11.99	20	0.92
EPU/ANX	45.78	56	0.83	22.55	20	0.31
RSS /ANX	48.11	56	0.76	19.07	20	0.52
UNCERT/ANX	52.97	56	0.59	24.09	20	0.24

Note: *p<0.1; **p<0.05; ***p<0.01