

INFORMATION AND ECONOMICS: A NEW WAY TO THINK ABOUT EXPECTATIONS AND TO IMPROVE ECONOMIC PREDICTION¹.

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The largely unexpected arrival of the global economic crisis and the largely unpredicted slowness of the recovery from the Great Recession should be precipitating an intellectual crisis across economics and policy making. We require additional theories and additional methods to detect how an economy is evolving and to provide the basis for policy intervention (Haldane, 2014).

Our starting point is a new theory of decision-making (Conviction Narrative Theory, CNT) and a new methodology for economic prediction (Directed Algorithmic Text Analysis, DATA).

The theory, like Keynes' theory of long-term expectations and Soros' theory of reflexivity, on which we draw, starts from observation and evidence. The method makes use of data sources and computer methodologies that have only become available in the last few years. It is derived from the theory, which focuses on how agents recruit their emotions when working out what to expect from their decisions and those of the agents around them.

In this approach expectations are conceived to be created through the capacity of human agents to simulate and communicate mental pictures of future outcomes that they *feel* are accurate. In this way, agents become confident enough to act to create potential gain and so risk loss under conditions of uncertainty.

The analysis of news media or other digital sources to derive systematic information about future expectations and behaviour is a feature only of the last fifteen years (Ramey and Shapiro, 1999; Romer and Romer, 2010; Dominguez and Shapiro, 2013; Baker, 2013, 2014; Choi and Varian, 2012; Haddow et al 2013).

The DATA method constitutes a highly specific approach to extracting information from a very large text databases by means of a dictionary or word search methodology.

CNT, which is rooted in contemporary advances in neurobiology, the theory of embodied and socially embedded narratives and our modern understanding of the role of emotion in cognitive processes, directs the word search towards just two very specific groups of emotion – those thought either to encourage or to inhibit action in conditions of uncertainty³. Specifically, the

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³ CNT is intended to provide a research framework for understanding important decision-making under uncertainty (Chong and Tuckett, 2014; Tuckett and Nolic, 2015). Although its overall focus on several evolved cognitive, affective and social processes is new, the importance of these processes, such as in established research in neurobiology (Damasio, 1994, 1999; Gallese, 2011), the story model (Pennigton and Hastie, 1992), attitude certainty (Gross, 1995), action readiness theory (Frijda, 1986; 2007), culture and cognition (DiMaggio, 1997), grounded cognition (Barsalou, 2008), trust research (Barbalet, 2011), and situated

emotion groups explored are those associated with excitement about gain (evoking approach) and anxiety about loss (evoking avoidance). Two dictionaries have been created containing pre-selected ordinary English words that evoke those emotions. The words have no direct economic content and will be shown to be orthogonal to any words characteristic of economic news in the text.

The outcome of using DATA to analyse a text database is a Relative Sentiment Shift (RSS) time series which captures changes in the relative strength of the two emotion groups just mentioned, from now on referred to simply as excitement and anxiety. RSS can be extracted from any unstructured text archive containing documents labelled with time and date. The underlying idea is that the texts capture shifts in emotional conviction in individual narratives which, when aggregated, can be conceived as indicators of overall shifts in confidence.

In this paper, after setting out details of our Directed Algorithmic Text Analysis (DATA) method for creating an RSS time series for the United States economy from the Thomson Reuters News Archive, we will describe analyses to demonstrate the following points:

I. Granger causality tests between RSS and the quarterly growth rates of real GDP (DLGDP), and real gross private domestic investment (DLK) show clearly that RSS Granger causes both DLGDP and DLK, but there is no causality from either DLGDP or DLK to RSS.

II. The relationship between RSS and DLGDP is not determined spuriously through a relationship with contemporaneous variables. In a linear regression of DLGDP on a set of forward looking variables based on asset prices, the lagged RSS series adds significant explanatory power.

III. The relationship between RSS and DLGDP/DLK is not explained by economic news within the news database. We look at this in two ways. First we confirm the words used to construct the RSS series are ordinary English emotion words, not changes in economic conditions. Second, we look at a number of ways of capturing news about changing economic conditions in the database, including the economic policy uncertainty index (Baker et al. 2013, 2014), and find they are Granger caused by the RSS with no causality in the reverse direction.

IV. The one period ahead forecasts of DLGDP of the Survey of Professional Forecasters (SPF) are known to be unbiased predictors (Stark 2010, for example). We confirm this result, but also show that RSS adds significant explanatory power to a regression of DLGDP on the consensus SPF forecasts.

V. In a linear regression of DLGDP on a set of forward looking variables based on asset prices, the contemporaneous and lagged values of the RSS series add significant explanatory power so that RSS may be useful for ‘nowcasting’.

VI. Finally, the RSS measure appears to give early warning of the 2008/09 economic recession. It shows a marked increase in the relative strength of anxiety, indicating a move into a low growth phase in the business cycle, well in advance of not only the consensus economic

simulation (Barsalou, 2003), has been highlighted within a variety of distinct research domains in recent years, albeit they have hitherto tended to be separated in silos. CNT is rooted in Max Weber’s methodological imperative to understand the meaning of action (verstehen) from the actor’s point of view (Weber, 1921 [1947]). Approaches based on verstehen differ from the main lines in contemporary cognitive science insofar as they emphasise that it is experienced or constructed reality that is constitutive of action (see for example, Parsons, 1937; Berger and Luckman, 1967; Giddens, 1984; Bourdieu, 1984) rather than the reality of the world per se. In other words in these approaches the information about the world actors process prior to making decisions rest not on given facts but on subjective interpretation of relevant evidence by the individual who functions in a social context. Information, therefore, is constituted, not given in and of itself.

forecasts, but of indicators such as the Anxiety Index reported by the Federal Reserve Bank of Philadelphia.

Section I describes the data and the method of constructing the RSS series, and compares and contrasts it with text based measures of sentiment and uncertainty already in the economics literature. Sections II-VII set out the empirical results. Section VIII contains a concluding discussion setting these ideas and findings alongside a discussion of how expectations should be modelled.

I METHOD AND DATA

I.A Background

We offer a new approach to text and sentiment analysis using algorithms directed by a specific theory of conviction. Machine learning algorithms are by now a well-established approach to content analysis within a document set. They offer the potential to carry out rigorous, very rapid and extensive analysis of large volumes of textual material in order to derive knowledge (for example, Pang & Lee, 2005; Sebastiani, 2002; Turney, 2002, Tetlock et. al., 2008, Soo, 2013). Because analysis is of documents fixed in “real time” it requires no revision. So, in contrast to economic indicators like GDP, which are estimated and revised, results are what they are.

Choi and Varian (2012) have used Google search data to predict a range of economic indicators. That approach depends on the argument that changes in search behaviour (for example for job vacancies) are stable indicators of developments in the economy (for example, alterations in employment rates). This assumption was undermined in efforts to use Google data to predict influenza outbreaks (Lazer et al, 2014, Bentley et al. 2014). Other approaches look at news content which may be expected to influence agent expectations and behaviour. Ramey and Shapiro (1999) used news reports to identify changes in government spending likely to impact the economy. Romer and Romer (2010) analysed text sources (including presidential speeches) to measure the likely effects of tax changes. Dominguez and Shapiro (2013) analysed newspaper and media sources to detect narrative shifts that could account for the slowness of the economic recovery. Soo (2013) went beyond simple news content to quantify the positive and negative tone of housing news (adapting the Harvard IV-4 word lists for Increase and Rise) in local newspaper articles about the US housing market, trying to isolate the roles of sentiment and fundamentals. In the UK the Bank of England, taking the view that perceived levels of uncertainty influence agent behaviour, has recently started to publish an uncertainty index based on a range of public information (Haddow et al, 2013). For the US Baker et al (2013, 2014) have described a method to construct an uncertainty index, based on analysing the presence of uncertainty words in news media. The underlying idea in most of these studies is that changes in information about the economy may alter expectations and so behaviour in it. Only Soo, using a dictionary approach and also looking at the co-occurrence of emotion words and economic news about what she called “fundamentals”, has tried to isolate the impact of emotion. Her work was limited to housing price rises during the recent bubble.

Other papers in the economics literature have used computerized textual analyses. For example, Gentzkow and Shapiro (2010) develop a method to compare phrase frequencies in newspapers with phrase frequencies in the 2005 *Congressional Record* in order to identify whether the newspapers’ language is more similar to that of a congressional Republican or a congressional Democrat. Jensen et al (2012) also look at political polarization. Their method, based on Gentzkow and Shapiro’s approach, was to construct “trigrams” (phrases) to compare the *Congressional Record* and the Google Ngrams corpus. Other recent examples include work by Hansen et al (2014) who used using machine learning linguistic techniques to analyse the

FOMC transcripts and Lucca and Trebbi (2009) who developed what they described as a new automated, objective and intuitive scoring technique to measure the content of central bank communication about future interest rate decisions based on information from the Internet and news sources.

In finance a research tradition of analysing texts using a dictionary approach to search for words with positive and negative emotional content⁴ has been developing (for example, Tetlock 2007). However, Loughram and McDonald (2011) have shown that for the analysis of 10k and similar documents general positive and negative valence word lists performed less well than those they developed specifically for the analysis of financial documents. Although, their published word lists for different emotional valence contain many thousands of words⁵ there are not yet any reports of their use in an economics context.

1.B The RSS emotion word list

We construct our Relative Sentiment Shift (RSS) index using a particular type of algorithmic text analysis allied to a dictionary approach. The algorithm does not use natural language processing and is not set to learn from the text. Rather, it is *directed* to search just for distinct groups of emotional words. In consequence it can work unmodified on any text database.

As noted above, the RSS aim is to capture emotional *shifts* in narratives circulating within an economy with the aim of capturing shifts in conviction, conceived as made up from a balance of approach and avoidance stimulating emotions.

The word list which the algorithm uses to measure the extent of conviction is directed in advance by our theory of narrative conviction (CNT) and remains unchanged. It is orthogonal to the events that may be being described. It is made up of ordinary everyday emotion words belonging to only two limited and pre-defined lists of words. Each list is about 150 words, one representing excitement about gain (approach) and the other one representing anxiety about loss (avoid). Twenty randomly drawn example words can be found in Table 1. Further details of the word list are in the supplemental material.

Table I

Randomly Drawn Selection of Words indicating excitement (about gain) and anxiety (about loss)

Anxiety	Anxiety	Excitement	Excitement
Jitter	Erodes	Excited	Perfect
Threatening	Uneasy	Incredible	Win
Distrusted	Distressed	Ideal	Amazes
Jeopardized	Unease	Attract	Energizing
Jitters	Disquieted	Tremendous	Gush
Hurdles	Perils	Satisfactorily	Wonderful
Fears	Traumas	Brilliant	Attracts
Feared	Alarm	Meritorious	Enthusiastically
Traumatic	Distrusting	Superbly	Exceptionally
Fail	Doubtable	Satisfied	Encouraged

The idea that approach and avoidance words were creating the conviction to act was derived from a cross disciplinary analysis of interview transcripts with fund managers (Tuckett, 2011). The theory that emerged draws on a growing body of work in social and brain science which underlines the facilitating role of emotions in decision-making, particularly when decisions

⁴ The technical term in the psychology literature is ‘valence’

⁵ http://www3.nd.edu/~mcdonald/Word_Lists.html

“matter” and their outcomes are uncertain (Chong and Tuckett, 2014; Tuckett, Smith and Nyman, 2014; Tuckett and Nikolic, 2015). Based on this idea, the specific words to be included in the algorithm were first selected by one of us (DT) from very much longer lists of categories of related emotion words in the Harvard IV-4 list⁶. The selection was intended to capture words judged to belong in either the theoretically important emotion group of excitement about gain (evoking approach) or anxiety about loss (evoking avoidance). The list so drawn successfully identified groups in different states of mind in an earlier analysis of the Enron email database (Tuckett, Smith and Nyman, 2014).

To check further whether words in the two lists evoked the relevant emotions Strauss (2013) set up an online experiment using Burke and James’s (2006) recommendations for giving instructions. 125 words (68 for anxiety, and 57 for excitement) were presented to subjects derived from the word list but using only the lemmas of those words i.e. the not inflected base forms as one finds them as entries in dictionaries. Previous work has established that emotional values generalize to inflected forms, which makes it unnecessary to rate all forms separately (Warriner et al, 2013). In line with Loughran and McDonald’s result that words may be understood slightly different in an economics/finance context respondents with a finance background were selected and further steps were taken to define excitant for subjects as “a state of anticipation of pleasure and triumph, as about future gains” and anxiety as “a state of uneasiness and apprehension, as about future uncertainties or losses”. Each word was presented separately to subjects on the centre of the screen and the order of the words was randomized for each subject.

Those who took part were randomly assigned so that they either rated words offered them for anxiety or words for excitement on a virtual scale. The results show (after standard procedures for removal of outliers) that a word rated highly by one participant on a particular scale was usually rated highly by other participants too. Additionally, there was a strong negative correlation between the mean ratings for anxiety and excitement⁷, indicating that participants could clearly distinguish between anxiety and excitement words (Strauss 2013).⁸

A crucial point to emphasise again is that the two word lists used to construct RSS do **not** contain any specific economic terms such as ‘crisis’, ‘boom’ or even ‘boost’. Rather they are what we might term regular English words, words in everyday use in a wide variety of contexts which convey the emotions of either ‘excitement’ or ‘anxiety’. Emotion measurement focusing on the use of words is justified by robust findings in social psychology which suggest that individuals, immersed in their culture and language, acquire automatic associations between words or symbols and their (emotional) meaning. For instance, emotional word perception goes along with affective reactions before the meaning of the word is more deliberately processed (Murphy and Zajonc, 1993; Siegle, Ingram and Matt, 2002; Hofmann et al, 2009). Additionally, emotionally-charged words have been shown to be attention grabbing, to facilitate reaction times and accuracy in decision tasks, and to be more easily recognised and remembered compared with neutral words (Ferr , 2003; Anderson, 2005; Sutton et al, 2007; Monnier and Syssau, 2008; Kousta, Vinson and Vigliocco, 2009). Emotional words also cause distinct neural activity (Kensinger and Schacter, 2006; Herbert et al., 2009; Anderson and Phelps, 2001).

I.C The RSS Statistic.

⁶ The Harvard IV-4 dictionary is available at www.wjh.hamecat.htmrvard.edu/~inquirer/ho

⁷ $r(262) = -0.809, p < .0001$

⁸ See supplementary material (Section 2).

Given the word list, we extract RSS as a summary statistic of the two emotional traits from text data by counting the two types of words within articles over a quarter.

Specifically, for the summary statistic of a collection of texts T we count the number of occurrences of excitement words and anxiety words and then scale these numbers by the total text size in number of characters. To arrive at a single statistic, highly relevant to the underlying theory of conviction narratives, we subtract the anxiety statistic from the excitement statistic.

$$Sentiment[T] = \frac{|Excitement| - |Anxiety|}{size[T]}$$

Data for all three data sets are available daily but in this paper we report results on a quarterly basis⁹. In other words, we aggregate the daily series in order to generate a quarterly series. We make the obvious remark that an increase in this relative emotion score is due to an increase in excitement and/or a decrease in anxiety.

Also, as evidenced by the definition of the measure we do not control for possible negations of our words, e.g. ‘not anxious’, ‘not excited’ nor do we control for their typical (expected) frequencies in ordinary usage. Nonetheless we did devise a test to explore the influence on results if “not” is present finding it made no difference¹⁰.

The simplicity of this method is intentional. It leads to clarity about what is measured and allows us to bring a range of statistical techniques to bear on correlations. To maintain clarity we have not yet taken advantage of sophisticated natural language processing techniques. We have also not employed approaches (e.g. Hansen et al, 2014, Socher et al, 2014) that use unsupervised learning to detect if the algorithm can learn from a pre-categorized database and rely on fitting to a pattern to make improved predictions. In future studies such techniques could be used to try to optimise the power of RSS, as for example by employing NLP (in an innovative manner) to help understand the emotional intent of words, or by using learning from data sources to weight some words more heavily than others. However, such approaches must be specifically developed to maintain the orthogonality of RSS to domain or data source specific words, and avoid data fitting.

1.D Data

We have discussed how we analyse content above. Here, we describe the source documents we selected to analyse.

There are a variety of text data sources with a macroeconomic and financial sector focus. For our purposes any text database thought to contain relevant data with a bearing on relevant economic narratives with documents labelled with time and date would suffice. In other studies we have successfully used Email data, Market Commentary prepared by analysts at the Bank of England, Broker reports held at the Bank, Newspaper or Internet content, and Twitter (Tuckett, Smith and Nyman, 2014; Nyman et al, 2014). The analysis in this paper is based on the Thomson-Reuters News Archive (RTRS).

The Reuters News archive consisted of articles published 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) within the ‘tags’ field were removed¹¹.

⁹ See supplementary material section 4.

¹⁰ Supplemental material section 6.

¹¹ Supplementary material section 3.

II GRANGER CAUSALITY OF GDP

We explore whether the RSS series constructed Granger causes changes in US GDP growth or vice versa.

II.A Methodology

We use the methodology described in Toda and Yamamoto (1996). In outline, in investigating Granger causality between any two series, this is as follows:

- I. 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 Kwiatkowski-Phillips-Schmidt-Shin (1992) tests. Let m be the maximum order of integration found.
- II. 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
- III. Check the stability of the VAR (we use OLS-CUSUM plots, which are reported in the Supplement).
- IV. 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.
- V. Add m extra lags of each variable to the VAR.
- VI. 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.

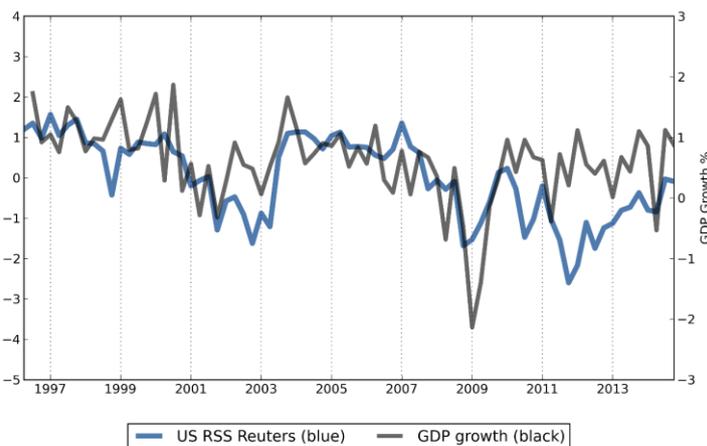
We used the statistical program R to carry out the analysis, and the various packages used to carry out the above Toda-Yamamoto procedure are documented in the Supplement.

II.B Granger causality of GDP and its main components

RSS assesses shifts in the relationships between two clusters of expressed emotion words based on the theory of conviction narratives and so in a conceptual sense entirely orthogonal to “economy” words evoking emotion that might also exist in the texts. Figure 1 plots the relationship between real quarterly growth in US Gross Domestic Product and the RSS series

Figure I

Quarterly percentage changes in US Real GDP and Relative Sentiment Shifts in Reuters US based News Articles 1996-2014 (Source: Thomson Reuters News Archive)



Using the methods outlined in steps I – VI above, we consider Granger causality between the RSS series and the quarterly change in real GDP, real gross private domestic investment, and real personal consumer expenditures¹² (DLGDP, DLK and DLCE). The data is quarterly, and the full sample period used is 1996Q1 through 2014Q3 in all tests reported on Granger causality. The details of the tests carried out are described in the Supplement. Here, we report step VI, namely the Wald tests of Granger causality.

Table II
Wald test statistics of Granger-causality between the relative sentiment shift series (RSS) and USDLGDP, DLK and DLCE

Direction	Chi-Sq	d.f.	p-value
RSS -> DLGDP	3.5	1	0.06*
DLGDP -> RSS	0.037	1	0.85
RSS -> DLK	2.9	3	0.086*
DLK -> RSS	0.94	1	0.33
RSS -> DLCE	0.14	1	0.99
DLCE -> RSS	5.2	3	0.16

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

The results in Table II show that there is evidence of Granger causality from the RSS series to both DLGDP and DLK. The Wald statistics in each case are significant at a p-value of < 0.10.

There is no evidence of Granger causality either way between RSS and DLCE. This is consistent with the hypothesis of Hall (1978) regarding consumer spending. It is also consistent with the psychological theory of decision making which underpins the RSS series. In contrast to investment decisions, most consumption decisions relate to items which are routine, low cost, have little implications for the future, and are easily reversed (e.g. if you buy a brand of baked beans which it turns out you dislike, you can buy another brand next week). So the level of uncertainty around the consequences of most consumption decisions is inherently much lower than it is around investment. We would therefore not expect the RSS series to cause consumer spending.

III ASSET PRICES

In terms of claiming causality from RSS to GDP, the question arises as to whether the result is spurious; perhaps the RSS series is simply capturing the effects of forward-looking indicators, such as asset prices. To explore this possibility we conducted further analyses taking as the dependent variable the first difference of the natural log of real quarterly US GDP (expenditure measure, denoted by DLGDP). We then considered the potential causal role of forwarding looking indicators choosing the following series, using the quarterly average values for each:

- The Michigan Consumer Sentiment Index (MCI)
- Changes in stock prices, measured by the Standard and Poor’s 500 (DSP)
- The yield on 10 year US government bonds (BOND)
- The yield on 3 month US Treasury bills (TB)
- The TED spread (TED)

¹² The data source is Table 1.1.6 of the NIPA tables at www.bea.gov

- The VIX, the Chicago Board Options Exchange Market Volatility Index

To do this we initially estimated a completely general equation containing each of the above variables at lags through 3 and the dependent variable at lags 1 through 3.

$$(1) DLUSGDP_t = \alpha + \sum_{i=1}^3 [\beta_i MCI_{t-i} + \gamma_i DSP_{t-i} + \delta_i BOND_{t-i} + \theta_i TB_{t-i} + \phi_i TED_{t-i} + \rho_i VIX_{t-i} + \lambda_i DLUSGDP_{t-i} + \kappa_i RSS_{t-i}] + \epsilon_t$$

As a first step, we eliminated all variables for which the null hypothesis that the coefficient is zero could only be rejected at a p-value greater than 0.75. We then eliminated further variables one at a time, in each step leaving out the one with the highest p-value.

The resulting regression is set out in Table III. The dependent variable is $DLGDP_t$, the sample period is 1997Q1 through 2014Q3.

Table III

*Preferred linear regression of real US GDP on asset prices and lagged values of RSS
Dependent variable: DLGDP; Sample period: 1997Q1 through 2014Q3*

Variable	Estimated coefficient	Standard error	p-value
Constant	0.0075	0.0011	6.5e-09***
$RSS_{t-1} - RSS_{t-2}$	0.0036	0.0011	0.002***
RSS_{t-3}	0.0018	0.0006	0.007***
$TED_{t-1} - TED_{t-2}$	-0.0103	0.0025	7.4e-05***
TED_{t-3}	-0.0045	0.0017	0.009***
DSP_{t-2}	3.8e-05	9.1e-06	9.0e-05***

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

Residual standard error: 0.0051; Adjusted R-squared 0.402. Test statistics and p-values: DW = 1.81 (0.16); Ramsey F (2, 63) = 1.07 (0.35); BG(4) = 0.85 (0.93); KS = 0.098 (0.47). The p-values for the test statistics are the p-values at which the null hypothesis is rejected. DW is the Durbin-Watson test for first order autocorrelation; Ramsey is the Ramsey RESET specification test; BG is the Breusch-Godfrey test of residual autocorrelation from 1 through 4 lags; KS is the Kolmogorov-Smirnov test for the normality of the residuals.

For the difference terms in RSS and TED, the null hypotheses that the relevant coefficients in each case were equal but of opposite sign were not rejected. The equation is well specified econometrically.

Both the RSS series and series related to asset prices have explanatory power in predicting short-term changes in real US GDP. When the above equation is estimated leaving out the RSS terms, the adjusted R-squared falls to 0.278, compared to the 0.402 of the equation above. So the incremental increase is 0.126 in absolute terms, or 45 per cent of the R squared when the RSS terms are omitted. On this analysis the RSS index does contain valuable new information.

IV ECONOMIC NEWS

As noted, above, the RSS series is constructed on psycholinguistic principles selecting English language words which evoke emotions in two emotional clusters. But a large news database like Reuters will include a number of more specific economic forecast words which evoke

emotion (for instance uncertainty, boom, etc.) or bits of economically relevant factual information which, in principle, might be correlated with RSS or even causal of its shifts.

In this section we examine the question as to whether the relationship between RSS and DLGDP is explained by economically relevant information within the news database rather than by shifts in emotion. We looked at this possibility in two ways. First, we looked carefully at the words used to construct the RSS series to confirm that what is measured are ordinary English emotion words, not changes in economic conditions. Second, we looked for words containing information about changing economic conditions and explored what relationship they had to changing sentiment.

First, looking carefully at the two lists of words we used to construct RSS, selected as emotional indicators via expert guidance validated in experiments, we find that all but six of the words selected seem unequivocally free of potential economic information. The six possible words which have both emotional and economic meaning are the words ‘uncertain’ and ‘uncertainty’ in the anxiety dictionary and the words ‘boost’, ‘boosted’, ‘boosts’, ‘exuberance’ and ‘exuberant’ in the excitement dictionary¹³. These words certainly indicate emotions but, arguably, also convey information about economic conditions – uncertainty, for instance, could be a reason to delay investment, exuberance to join in. To test whether these words might be influencing the results we re-examined the relationship between RSS and GDP leaving these words out of the RSS measure. The new series correlated with the original RSS series at 0.99 in level form and 0.99 in difference form making no difference to the results reported above¹⁴. The result appears to confirm that the RSS measure is an independent variable.

A second way we have attempted to examine the possibility that the correlation between RSS and GDP is the outcome of changes in economic news rather than emotional shifts, has been to examine the relationship between RSS and three relevant economic indicators:

- I. The widely quoted Economic Policy Uncertainty Index (EPU) (Bloom,2014, Baker et al, 2012) which captures discussions of uncertainty in major newspapers in the US.
- II. A simple series (UNCERT) in which we counted the number of times each day the words ‘uncertain’ and ‘uncertainty’ appear in the Reuters news archive for the US.
- III. A further simple index (‘ECON’) we constructed to capture more specifically economic terms, namely ‘boost’ and ‘boom’ (positive emotion words) and ‘crisis’, ‘recession’ and ‘fall’ (negative emotion words). A summary score indicates whether economic news for that quarter is shifting in a positive or negative direction over time.

We then conducted two sets of Granger causality tests. The first, we look at the influence of each variable on GDP and, the second, to look at the causal relationships between the variables themselves and RSS. We report results with quarterly data, because this is the periodicity of the national accounts.

Table IV

Wald test statistics of Granger-causality between the Economic Policy Uncertainty Index (EPU), UNCERT, ECON and DLGDP

Direction	Chi-Sq	d.f.	p-value
EPU -> DLGDP	1.2	1	0.27

¹³ See Table 1. Also Table A1 in the Supplementary material contains a further 40 anxiety and 40 excitement words selected at random from the total. The full list can be obtained from the authors on request.

¹⁴ Supplementary material page section 7.

DLGDP -> EPU	0.44	1	0.51
UNCERT -> DLGDP	3.3	1	0.07*
DLGDP -> UNCERT	0.28	1	0.6
ECON -> DLGDP	0.38	1	0.54
DLGDP -> ECON	1.3	1	0.25

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

Table IV looks at the ability of these three new variables to predict changes in DLGDP (as in Table II above) using the Wald test. There is no evidence of Granger causality of GDP from either the EPU or the ECON variable. Interestingly, compared to the sophisticated EPU measure, the simple UNCERT variable shows some evidence of Granger causing GDP.

Table V

Wald test statistics of Granger-causality between the relative sentiment shift series (RSS) and UNCERT, ECON and EPU

Direction	Chi-Sq	d.f.	p-value
RSS -> UNCERT	15.5	1	8.3e-05***
UNCERT -> RSS	1.6	1	0.21
RSS -> ECON	15.3	2	0.0005***
ECON -> RSS	4	2	0.13
RSS -> EPU	19.7	2	5.2e-05***
EPU -> RSS	1.5	2	0.48

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

Table V reports the Granger causality tests (using the Wald test as before) we undertook between the three new variables and RSS. It is clear that EPU, UNCERT and ECON are all Granger caused by RSS but not vice versa.¹⁵

V PROFESSIONAL FORECASTS

The RSS series also appears to add credible information to improve the one-quarter ahead forecasting record of real GDP growth in the United States.

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. Data on the consensus forecast for one-quarter ahead real GDP growth is available at <http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/RGDP/>¹⁶. A discussion of the historical accuracy of the forecasts, for both GDP and other economic variables, is given in Stark (op. cit.).

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

¹⁵ We report quarterly data because this is the periodicity of the national accounts

¹⁶ Using data downloaded from the click through "Annualized Percent Change of Mean Responses"

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 1996Q2 through 2014Q3.

Table VI

Regression of the actual values of quarterly growth in real US GDP (DLGDP) on the consensus forecast made in the previous quarter (SPF) and the relative sentiment shift series (RSS)

Dependent variable:		
	DLGDP (1)	DLGDP (2)
Constant	-0.430 (0.798)	0.325 (0.829)
SPF	1.124*** (0.290)	0.829*** (0.271)
RSS		0.765** (0.299)
Observations	74	74
R2	0.170	0.240
Adjusted R2	0.159	0.219
Residual Std. Error (df = 70)	2.469	2.379
F Statistic	14.77*** (df = 1; 72)	11.23*** (df = 2; 71)

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

The RSS variable is statistically significant from zero, and the adjusted R squared increases from 0.159 in the equation without RSS to 0.219 when it is included, an incremental effect of 38 per cent.

The same results hold when the third vintage estimate of GDP is used rather than the latest data used in Table VI¹⁷.

VIII ‘NOWCASTING’ GDP GROWTH

A further way in which RSS seems to be of value is for nowcasting. First estimates for GDP in any given quarter are available from national statistical offices some weeks after the quarter ends. They are subsequently revised sometimes even several years later (Ormerod 1978, Shrestha and Marini, 2013, Manski 2014). Estimates are often influenced by the state of the business cycle at the moment they take place so that, for example, in the case of 2008, the move into negative growth which took place during the year was not recognised in revised statistics until about a year later (Shrestha and Marini, 2013). Efforts are underway to improve this situation by “nowcasting” using new data sources such as Google searches (Scott and Varian, 2012) but they are not necessarily reliable (Lazer, et al. 2014, Ormerod, Nyman & Bentley, 2014).

Our analysis suggests RSS could provide statistically reliable information to assist nowcasting of this kind. For the US, we again begin with equation (1) above, except that we add the

¹⁷ See the supplementary material section 11.

contemporaneous value of all the series as well as their lagged values. All of them will be known for certain at the end of the relevant quarter. We followed the same process, namely eliminating all variable where the p-value was above 0.75, and then eliminating them one at a time on a step by step basis. Results are in Table VII. The dependent variable is $DLGDP_t$ sample period is 1997Q1 through 2014Q3.

Table VII

Preferred linear regression of real US GDP on asset prices and contemporaneous and lagged values of RSS. Dependent variable: $DLGDP_t$; Sample period: 1997Q1 through 2014Q3

Variable	Estimated coefficient	Standard error	p-value
Constant	0.0074	0.0011	1.4e-08***
$RSS_t - RSS_{t-2}$	0.0020	0.0010	0.061*
RSS_{t-3}	0.0023	0.0006	0.0005***
$TED_{t-1} - TED_{t-2}$	-0.0092	0.0025	0.0004***
TED_{t-2}	-0.0045	0.0017	0.0073***
DSP_t	2.4e-05	1.0e-05	0.023**
DSP_{t-2}	2.7e-05	9.2e-06	0.0047***

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

Residual standard error: 0.0046; Adjusted R-squared 0.527. Test statistics and p-values: DW = 1.85 (0.18); Ramsey F (2, 62) = 2.70 (0.075); BG(4) = 2.36 (0.67); KS = 0.075 (0.78). The p-values for the test statistics are the p-values at which the null hypothesis is rejected. DW is the Durbin-Watson test for first order autocorrelation; Ramsey is the Ramsey RESET specification test; BG is the Breusch-Godfrey test of residual autocorrelation from 1 through 4 lags; KS is the Kolmogorov-Smirnov test for the normality of the residuals

For the difference terms in RSS and TED, the null hypotheses that the relevant coefficients in each case were equal but of opposite sign were not rejected. The equation is again well specified econometrically. The value of RSS at time t is indeed statistically significant in the regression, though its value at lag 2 has the equal but opposite sign. Compared to the equation using only lagged values as explanatory factors, the adjusted R-squared increases from 0.402 to 0.527.

VII TURNING POINTS AND PHASES

We examine the causality between the Anxious Index (ANX) reported by the Federal Reserve Bank of Philadelphia¹⁸ and RSS. ANX is based on a survey of professional forecasters, which asks panellists to estimate the probability that real GDP will decline in the quarter in which the survey is taken and in each of the following four quarters. The anxious index is the probability of a decline in real GDP in the quarter after a survey is taken.

We define two variants. We let ANX in period t be defined by the probability of recession in period t (as estimated in period $t-1$). We let ANXA in period t be defined by the probability of recession in period $t + 1$. In other words, ANXA in period t is the same as ANX in period $t + 1$.

¹⁸ <http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index/>

The data is quarterly, and the full sample period used is 1996Q1 through 2014Q3. Again, the details of the tests carried out in steps 1 – 5 of the Granger causality procedure are described in the Supplement. We simply report here step 6, namely the Wald tests of Granger causality.

Table VIII

Wald test statistics of Granger-causality between the relative sentiment shift series (RSS) and ANX and ANXA

Direction	Chi-Sq	d.f.	p-value
RSS -> ANX	28.5	3	2.8e-06***
ANX -> RSS	0.85	3	0.84
RSS -> ANXA	20.3	2	3.9e-05***
ANXA -> RSS	2.1	2	0.34

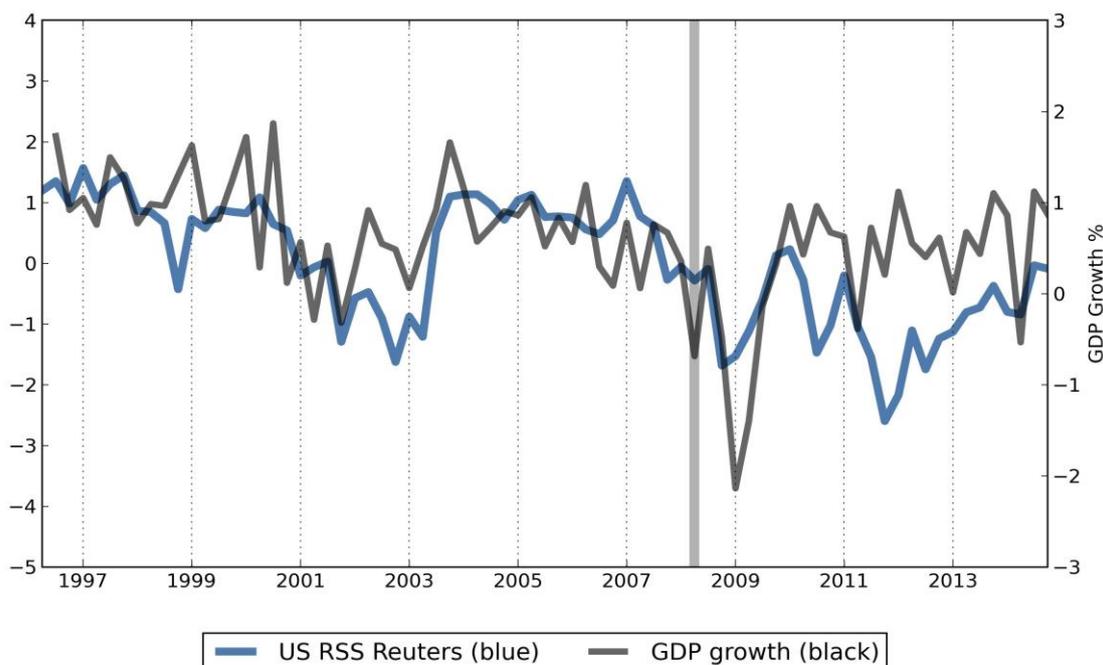
Note: *p<0.1; **p<0.05; ***p<0.01

There is very strong evidence of Granger causality going from RSS to both the Anxiety series, and no evidence of causality in the reverse direction.

A further set of results suggest the RSS series can also be useful for determining when turning points in the economy appear imminent, something which until now has proved very difficult.

Figure II below shows the RSS time series (solid line) plotted with US GDP (broken line). The solid line in the centre marks the moment – not forecasted at the time – when GDP began to shrink (2008Q1). The sharp downturn in RSS in mid-2007 is a clear turning point, so RSS in this example is a leading indicator for what subsequently happens to GDP.

Figure II
RSS and USDLGDP



Over the period 2003Q2 – 2007Q2, the mean value of the RSS series (scaled) was 0.850 with a standard deviation of 0.256. The value in 2007Q3 is 4.37 standard deviations (taking the 2003Q2-2007Q2 of the standard deviation) below this mean value. In 2007Q4 and 2008Q1 it is, respectively, 3.54 and 4.42 standard deviations below. A clear shift is identified.

The Anxious Index discussed above, indicating the probability of a recession in the next quarter, took values 2007Q3-2008Q1 of 13.14, 14.00 and 16.95 respectively, indicating only a low probability. It was not until 2008Q2 that the value rose to 42.9. The mean annualised growth rate of GDP in the Survey of Professional Forecasters made in 2008Q2 for 2008Q3 was +2.17 per cent. It was not until 2008Q4 that the consensus prediction for growth in the next quarter (2009Q1) became negative.

So the RSS series fell sharply below its levels in the mid-2003 to mid-2007 period in the third quarter of 2007, a fall which was subsequently sustained. Consensus economic forecasts were essentially of no value at all in predicting the recession, and the Anxious Index only showed a substantial increase in the probability of recession in the next quarter in 2008Q2. The only indicators which seem to have given a similar type of early warning are the Financial Stress Indices produced by the various Federal Reserve banks. Putting the data on a quarterly basis, the Cleveland Fed FSI, for example, takes a value of 0.85 standard deviations above its 2003Q2-2007Q mean in 2007Q3. An increase here means a rise in financial stress. In 2007Q4, it was 2.58 standard deviations above the 2003Q2-2007Q2 mean, and in 2008Q1 3.61 above. The St Louis Fed index was already 2.42 standard deviations above in 2007Q3, rising to 4.18 and 5.15 respectively in 2007Q4 and 2008Q1. However, Nyman et al. (2015) show that over a longer period (1996-2014) the RSS series Granger causes both the Cleveland and St Louis Financial Stress Indices.

We also find evidence that RSS may be of help in identifying different phases of GDP growth. We use cluster analysis of the data on quarterly US GDP growth and the Reuters RSS data over the period 1996Q1 through 2014Q3. We use the fuzzy clustering algorithm in the command ‘fanny’ in the statistical package R (Kaufman and Rousseeuw (1990)). Dunn’s partition coefficient (Dunn 1973) indicates that the data set is best described by just two clusters. Full details of analysis are available in the Supplement. Each cluster is made up of two sets of data which are essentially time-contiguous. One cluster comprises data from 1996Q1 through 2000Q3 and then from 2003Q2 through 2007Q2. The other contains the data from 2000Q4 through 2003Q2 and from 2007Q3 through 2014Q2¹⁹. The mean values of both real GDP growth and the RSS Reuters data are distinctly different in the two clusters. In the former, GDP growth at an annualised rate averages 3.62 per cent and 1.22 per cent in the second. The corresponding values for the normalised Reuters RSS data are +0.85 and -0.87 respectively.

In economic terms, the clusters identify relatively high and low growth regimes. The value of the RSS data can be calculated on the last day of each quarter, and is never subject to revision, since by that date all the articles in the quarter have been published. There is no overlap at all in the normalised values of the RSS data in the two regimes identified by the clustering. The maximum value in the low growth cluster is -0.031 and the minimum in the high is +0.030. So a very good heuristic for initial identification of GDP growth for the current quarter is given by the value of the RSS series.

VIII DISCUSSION AND CONCLUSION

¹⁹ There are one or two minor exceptions, with, for example, the quarter in which LTCM collapsed (1998Q3) being allocated to the second cluster.

We have described a new method of content analysis which identifies, very rapidly, shifts in the relations between two core emotional groups, excitement (about gain) and anxiety (about loss), in different sets of documents primarily containing economic and financial news. As we have emphasised the word lists which we use to measure these core emotion groups are essentially orthogonal to economic terminology. They contain no explicit economic terms, but are made up of everyday English words, validated for their emotional content in a psychological experiment.

In this paper we focused on GDP through analysis of the Reuters database. Other results have demonstrated causality versus the ViX and the Michigan Consumer Sentiment Index. The latter outperform those of the consensus forecasts and are much stronger using the more textually rich series of Broker Reports or Bank of England Market commentary we had available (Nyman and Ormerod, 2015; Nyman et al, 2015). The latter have more nuanced and arguably more relevant content and suggest the power of RSS might be stronger with still more suitable data. Other results are relevant to anticipating unforeseen financial risk (Tuckett et al, 2014; Nyman et al, 2015).

There is scope for much more work and the approach can be extensively developed both by using it to analyse databases more explicitly tailored to financial and economic news and through development of the methods themselves. For the time being it is clear that using Directed Algorithmic Text Analysis to capture Relative Sentiment Shifts does work as a predictor of a range of variables. The reason it works, we suggest, is because it successfully captures the emotion within narratives which people construct in order to make decisions under uncertainty. When this emotion shifts, the decisions agents are making are shifting and so economic activity shifts too.

Until now economics has focused almost exclusively on a model of human behaviour in which, on average, agents develop expectations and are able to assess the outcomes of their actions correctly. One limitation of that approach is that it must break down insofar as information contexts exist which are genuinely uncertain – i.e. in contexts which leave scope for intelligent agents to interpret information differently or to have different levels of commitment to the actions they consider appropriate. For example, in the context of macroeconomic models of the US economy, a major survey by Ramey (2011) shows that even in this rather narrow methodological context, the size of the fiscal multiplier, a basic concept in this area, varies between 0.8 and 1.5 according to whichever model one selects. Looking back to the policy debates in the immediate aftermath of the collapse of Lehman Brothers in September 2008, prominent economists, including Nobel Laureates, could be found on both sides of the argument as to whether or not to allow banks and other financial institutions to fail. It is hard to imagine that these groups of protagonists had the same model of the economy in mind.

More generally, within the statistics literature, there is a widespread understanding that model uncertainty is often an inherent feature of reality. It may simply not be possible to decide on the ‘true’ model (see Chatfield (1995).) In an economic context, Onatski and Williams (2003), in a survey for the European Central Bank of sources of uncertainty, concluded that “The most damaging source of uncertainty for a policy maker is found to be the pure model uncertainty, that is the uncertainty associated with the specification of the reference model”. Gilboa et al. (2008) note that “the standard expected utility model, along with Bayesian extensions of that model, restricts attention to beliefs modelled by a single probability measure, even in cases where no rational way exists to derive such well-defined beliefs”.

A second limitation of prevailing models is that they unnecessarily limit agents’ capacities and in doing so leaves out important causal variables, such as emotion, and so denude their explanatory capacity.

Human cognitive capacity evolved from an animal body and brain developed in a social context. The capacities and innovative achievements (and failures) we see around us are the product of a generally successful process of adaptation in a life saturated with complexity and uncertainty. Humans were not and are not reduced to paralysis when they cannot calculate. Moreover, they over-ride calculations and dispute statistical evidence successfully by judgement. The major issues facing the planet or the future organization of the economy cannot be successfully addressed within a simple optimisation format. 2008 should have taught us that.

A growing number of contributions across psychology and the brain sciences make the point that the evolution of language and simulation capacities greatly increased the complexity of human social life. They caused decisions to become more complex and difficult while at the same time opening up vastly new and improved possibilities for enlightened and co-operative decision-making (for example, Baumeister and Masicampo, 2010). From among these possibilities we stress how narrative, telling stories about what is happening to oneself and to others, offers a crucial means to imagine the future and, via embodied simulation, to “feel” and share the potential consequences of imagined actions and reactions. In this context emotion is a resource and action is the outcome of cognitive and affective processes working together. Human actors faced with genuinely uncertain contexts subjectively develop the confidence to risk loss and to act. Stressing the positive role normally played by narrative and emotion in decision-making produces a more scientifically grounded theory of expectation formation and so acts to counter a very old idea that reason and emotion are in conflict – unsubstantiated and contradictory two systems theories such as Kahneman’s being only the latest incarnation.

Conviction narrative theory sets out how under real uncertainty agents draw on their cognitive and affective endowment to reach conviction when calculation alone would be inadequate. In our framework, action in uncertain contexts is possible because the human capacities for emotion and narrative are allied with cognitive processes to create conviction; defined as a subjective sense of accuracy that gives structure to expected outcomes. Most crucially, we think of narratives as managing the opposed forces of approach and avoidance that the subjective experience of taking action in conditions of deep uncertainty necessarily creates. The factors that influence conviction, in part, are likely to be developed through social interaction. Agents, in short, are influenced by what they see others are doing and the norms and practices that grown up around them.

A number of new empirically-backed theories developing in sociology, economics, anthropology, psychology and neuroscience support such a broader model of human behaviour. Within such frameworks narrative and emotion can be conceived to join with cognitive and calculative skills to facilitate economic action (For example, Akerlof and Shiller, 2009; Bruner, 1990; Damasio, 1999; Lane and Maxfield, 2005; Mar and Oatley, 2008; Beckert, 2011, Barbelet, 2013; Pixley, 2009; Bandelj, 2009; Berezin, 2005, 2009; Tuckett, 2011). Moreover, because narratives are developed through social interaction theories of this sort provide new understanding - they create order or equilibrium not mechanically but via social action and so precisely in the fragile way emphasised in the Soros theory of reflexivity (Chong and Tuckett, 2014). The economy is “constituted”.

The methods we have described above show that a more rounded theory of expectation formation can be operationalised successfully and with advantage. They outperform existing forecasting models, even when these are liberally aided by judgmental overlay. Focusing on specific action-enabling (excitement) or disabling (anxiety) emotions in the narratives circulating in the economy helps us to understand its likely evolution. The explanation is that such narratives are drawn on to support actions in the economy (making expected outcomes

less unbearably uncertain) and so drive the aggregate outcomes of those actions, which subsequently emerge as GDP.

Two features of the prototype RSS measures developed to date should be stressed. First, even when a very large textual database is interrogated, the analysis can be performed quickly, enabling it to be used as a leading indicator for economic time series in a subsequent period. Given the database, the time needed to calculate the RSS is, at most, a few hours. Second, unlike many economic time series, the RSS is not subject to revisions. The Reuters newsfeed text database in any given month, for example, contains articles that are not revisited and revised; nor are additional articles added to it for that month.

Keynes (1936, 1937) argued that economic action is energised despite future uncertainties by a combination of conventional judgment and animal spirits. The RSS measure outlined is based on a modern social and brain science approach to the way action is taken under uncertainty. It can be considered an operational indicator of animal spirits.

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