Bringing Social-Psychological Variables into Economic Modeling: Uncertainty, Animal Spirits and the Recovery from the Great Recession[1]

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Abstract

Conviction narrative theory (CNT), a social psychological approach to the way economic agents take deisions under Knightian uncertainty, together with the new methodology of directed algorithmic text analysis (DATA), provide the opportunity for a theory of economic sentiment or animal sprits grounded in empirical facts. Applying DATA to the full text of the daily Reuters news feeds from January 1996 through November 2013, we derive an "animal spirits" series for both the US and the UK economy. Both series inform the movements in real GDP over the period. For example, in both countries there is a marked downturn in animal spirits in June 2007, well in advance of other indicators of the coming recession. The series may also explain why the subseqeunt recovery has been exceptionally weak from a historical perspective.

Keywords: animal spirits; radical uncertainty; conviction narratives; Great Recession; recovery; directed algorithmic text analysis
JEL Classification: C82, D83, D84, E32

1. Introduction

The ingenuity of macroeconomic theories and empirical modeling can obscure a fundamental fact. Namely, that the process of decision making by agents involves sentient and social human responses to information events as well as a willingness to commit to action. In this paper, we look beyond the assumptions which are generally made to bypass the potential impact both of radical uncertainty and psychological variables on such responses.

We present evidence that rigorous techniques now exist to take mental states and their influence on expectations into account. We illustrate the techniques with an explanation not only of the slow recovery from 2009 in both the US and UK economies, but of several key macroeconomic phenomena in both the US and the UK over the 1996-2013 period.

Macroeconomic formulations are often founded on theories about the impact on a representative agent of changing expectations based on the microeconomic view that behavior responds to optimal Bayesian updating of the impact of new information. Harstad and Selten (2013) argue, in that specific context, that 'the fundamental tool of neoclassical economics is an objective function that maps the space of all relevant decision variables into a scalar' (p.505).

Socio-psychological factors introduce the possibility that the same set of values for the same relevant set of decision variables are capable of more than one interpretation, and hence more than one possible course of action.

The decision context of ontological uncertainty (Lane and Maxfield, 2005) envisaged as important by Knight (1921) and Keynes (1921) produces similar difficulties. In this case

there is (*ex ante*) no knowable distribution of outcomes. The information value of each new item of information can only be imagined, with a level of conviction which itself may vary.

The limitations for modelling that are implied if one-to-one correspondence between information and expectations is removed is obvious. It has had the consequence that most economic models have maintained very constrained assumptions, in the hope that it is reasonable to assume the problem away.

However, it may still be the case that even under ontological uncertainty agents might respond in emotionally and socially systematically patterned ways. Economic sociologists, for example, argue that it is social-psychological factors embedded in the economy that allow it to work (Granovetter, 1985; Swedberg, 1993). Likewise social and psychological factors are argued to influence interpretations of information and expectation formation (di Maggio 1997, 2002)

We aim to show that rigorous modelling of agent responses to information is possible; specifically that emotional shifts in agents' responses to information can be operationalized with predictive consequences. Our approach has two key building blocks. First, it relies on the social-psychological theory of conviction narratives (Chong and Tuckett, 2014) in which emotion and narrative capacity are seen as significant resources to allow economic agents to act and not just as sources of error.   Second, we use new algorithmic text search methods based on conviction narrative theory (Tuckett, Smith and Nyman, 2014) to create what we term directed algorithmic text analysis (DATA) to extract patterns of meaning in narratives emerging from a large textual data base.

A point to emphasize is that we carry out directed algorithmic analysis of the textual data base. In other words, we do not follow approaches which use a more or less arbitrary list of words which might plausibly be held to convey different emotions, say optimism or pessimism and simply search for these. As we will outline, we do search for the appearance of particular words. But the psychological theory directs the search to words precisely indicative of just two emotions, namely 'excitement' and 'anxiety'. The selection of the sets of words which convey such emotions is both grounded in and directed by the underlying theory and validated in laboratory settings (for example, Strauss 2013).

The paper is organized as follows. First, we consider the growing interest in narrative and sentiment among some macroeconomists and how it has been approached, and then introduce Conviction Narrative theory. Second, after some discussion of other methods, we describe DATA, a new method for directed algorithmic text analysis, which we use to measure relative sentiment shifts within conviction narratives circulating within an economy, as reported in the Reuters News archive 1996-2013. Third, we present some results. Shifts in the time series reflect the impact of major events in the history of the US and UK economies. They suggest why the recovery from the recent recession has been weak, and give much earlier warning of the onset of recession than forecasters realized at the time. They also suggest that policy makers forestalled a major recession after the dotcom collapse and, further, they add explanatory power to an autoregressive model of GDP. We argue, therefore, that attention to the social-psychology of conviction narratives adds an important additional element to standard macroeconomic analysis.

2. Conviction Narratives

We can think of the economy as a system of coupled networks: a financial sector, non-financial companies, and individuals (consumers) (see for example Farmer et al. 2012). We can also suppose that a key feature which drives behavior in each of these sectors is a mental state supporting the capacity to take constructive long-term focused action within an economy at the current moment and to sustain such actions into the future. Some information on the necessary underlying mental states has been available for several decades in the various surveys of business and consumer sentiment such as the widely used Michigan Consumer Sentiment Index. But these are essentially both atheoretically constructed and, further, give meaningful information only about the current situation in the economy. To understand what economic agents might do in future we need to understand sentiment about *the future* and how they view it.

The importance of information about future sentiment is topical. Central banks are giving explicit attention to try to influence it by narrative guidance and a number of recent publications in the economic literature have shown that narratives circulating in the economy may be important macroeconomic indicators. For instance, Akerlof and Shiller (2009) set out some general principles as to the importance of narrative. Several other studies have carried out textual analysis. Romer and Romer (2010) examine the written record of Presidential speeches and Congressional reports to try to identify the motives for tax changes. Dominguez and Shapiro (2013) suggest the slow recovery of the US economy as indicated by forecast changes was linked to news events reported in the Wall Street Journal, Financial Times and elsewhere. Baker et al. (2013) measure policy uncertainty by a human audit of 5000 newspaper articles. Finally Soo (2013) provided evidence from an analysis of narratives in local newspapers that sentiment may have had a significant effect on the development of the US housing bubble.

The first three papers just cited present evidence about narratives based on human audits of documents. Soo's work is notable because she looks at sentiment in narratives going beyond traditional sentiment measures[2]. Drawing on finance and accounting research on content analysis of documents and news[3] and recent methodological developments (Tetlock, 2007; Loughram and McDonald, 2011), she employs several automated methodologies to measure positive and negative emotion in narratives about housing and to plot their relationship.

The choice of positive and negative affect has a history in behavioral economics, Emotion[4] is conceived in opposition to formal reasoning and as some kind of evolutionary residual contributing to automated "type 1" rather than "type 2" cognition (Kahneman, 2011). Whether two systems of this sort actually exist (Giggerenzer and Reiser, 1996; Keren and Schull, 2009); or more broadly what emotions are for, is controversial in brain science. As Elster (1998) set out in a review of the relevance of emotion to economy, the economist's view of emotion as in conflict with reason is certainly at odds with a great deal of thinking in modern science. The contemporary view of the brain essentially is of bundles of cells that support perception and action and so aid homeostasis and survival by constantly attempting to match incoming sensory inputs with top-down *prior* expectations or predictions (Clark, 2013; Friston et al, 2012, 2013). Emotions are conceived not as outdated obstacles but as a biologically evolved resource able to facilitate action (see Chong and Tuckett, 2014; Bandelj, 2009; Barbelet, 2011, Damasio, 1994, 1996, 199, 2000; Stets, 2010; Schull and Zaloom, 2011,

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[2] Such as mutual fund flows, dividend premia, the VIX index, surveys of home buyers, purchasing managers indices or consumer confidence indices, central bank soundings, etc.

[3] For example, Antweiler and Frank, 2004; Engelberg, 2008; Li, 2008. Jegadeesh and Wu, 2011; Hanley and Hoberg, 2010; Kothari, Li and Short, 2009; Feldman and Segal 2008; Henry 2008.

[4] For example, the "affect heuristic", endowment effect, optimism bias or loss aversion.

Frith and Singer, 2008; de Oliveira-Souza and Moll (2011); Lange, van Gaal, Lamme and Dehaene, 2011).

Conviction narrative theory is new in that it focuses on economic action, which is dependent not just on information but commitment. It builds on the view of emotion as a resource and narrative as a largely successful way of apprehending complex and uncertain situations so that they create conviction and a sense of truth (Bruner, 1986, 1990, 1991; Mar and Oatley, 2008). The theory was used to understand money managers. They described the context in which they work as one in which they *must* act although *ex ante* relevant available information – for example about currencies, growth rates, the future of the Euro, firms' prospects and so on - was open to multiple interpretations. To act, they had to imagine the future price path of the entities in which they were interested (Tuckett, 2011, Chong and Tuckett, 2014) and to overcome their ambivalence (Smelser, 1998; Pixley, 2009; Tuckett and Taffler; 2008), that is to say the emotional conflicts their situation created.

Emotional conflict is unavoidably triggered when economic actors have to make and sustain decisions over time. This is because their actions make them dependent on uncertain outcomes, which necessarily generate both anxiety about possible future loss and excitement about possible future profit. In order to act the imagined outcomes must excite sufficiently that any hypothetical doubts about the actions' future potential to create loss are overcome. Conviction narratives achieve the necessary support for action. Money managers think through "conviction narratives" which contain combinations of attractor and/or doubt repelling elements. Insofar as narratives contain a balance of excitement over anxiety, their narrative hypotheses allow financial

actors to feel committed to their beliefs and to manage dependency on the uncertain future.

The uncertain context faced by money managers applies to any economic agent required to act and facing profit or loss in consequence when the future is some way off and uncertain. To act they require a conviction narrative. We define conviction as a state of mind of an individual and confidence as an emotional state belonging to a collective, such as a group or financial market (Chong and Tuckett, op.cit.). We then think of a conviction narrative as an internal representation of each agent's environment that allows the agent to feel convinced enough to act in an uncertain context and to feel comfortable to sustain that action, although the future outcome of that decision is unknowable. We can also think of the collection of conviction narratives within the economy or its different sectors as expressing the current state of narrative confidence *about the future*.

In the next section we will discuss how we derive overall indices of shifts in the quantity of excitement and anxiety present in narratives about the economy, drawing on conviction narrative theory. The index of net excitement versus anxiety in narratives within an economy can be treated as an empirical measure of Keynes' concept of animal spirits.

3. *Directed Algorithmic Data Analysis (DATA)*

Machine learning algorithms offer the potential to carry out rigorous and extensive analysis of textual material in order to derive meanings and narrative from it (Hofmann, 2001; Ikonomakis, Kotsiantis & Tampakas, 2005; Pang, Lee & Vaithyanathan, 2002; Pang & Lee, 2005; Sebastiani, 2002; Turner, 2002). Our approach has been to develop

algorithms to analyze an archive of the daily Reuters news feeds published from the London and New York offices from 1 January 1996 through 30 November 2013, excluding articles classified by Reuters as about sport, the weather and "human interest".

The Reuters news archive is preserved for analysis in the form of CSV files of monthly collections of articles from a variety of publishers, including Reuters. At the time of our analysis it contained over 16 million English articles spanning the period from January 1996 onwards. Reuters provides extensive documentation of the various columns in each file, but here it suffices to note that we have made use of the 'date', 'language', 'text', 'attribution' and 'tags' fields. The 'date' field contains the publication date, the 'language' field the publication language, the 'text' field the main article text, the 'attribution' tag states the publisher and the 'tags' field contains a comma separated list of article tags provided by Reuters.

We consider only articles with RTRS (Reuters) as the attribution and English as the language. To separate out articles published in the London office, which we define as UK focused, we consider only those articles where the text field starts with 'LONDON'. To separate out articles published in the New York or Washington offices, which we define as US focused, we consider only those articles where the text field starts with 'NEW YORK' or 'WASHINGTON' respectively. Finally, to avoid articles tagged as 'Sport', 'Weather' or 'Human interest' we remove articles with tags SPO (sports), ODD (human interest) or WEA (weather) within the 'tags' field.

A formal exposition of the methods we use to create relative sentiment shifts or "animal spirits" time series from this data can be found in the appendix. To summarize, we aggregate the two collections of UK and US articles into two monthly series by the

publication date, leaving us with approximately 7700 and 10100 articles per period in the UK and US respectively. For each monthly collection of articles we compute two emotional summary statistics, one for *excitement* (the attractor) and one for *anxiety* (the repellor), by applying a simple word count methodology. Two sets of emotion words, each of size approximately 150, indicative of the relevant emotions have been defined. The lists proved useful in other studies (Tuckett, Smith and Nyman, op cit.) and have been validated in a laboratory setting (Strauss, 2013).

The relevant "emotion score" (excitement or anxiety) is computed as the average number of defined emotion words per article found in the given monthly collection of articles. The next step, to measure animal spirits in the content of narratives within the collection, is to compute the difference between the attractor (exciting) and repellor (anxiety) emotion scores. For all articles published in month t we arrive at a value of animal spirits assigned to the 1st of month $t+1$. For the formal definitions we refer to the appendix.

4. Results and Disussion

Figures 1 and 2 plot, respectively, our measure of animal spirits for the US and the UK over the period January 1996 through November 2013. The series are normalised in order to make them directly comparable.

Animal Spirits in the US
January 1996 through November 2013

Animal Spirits in the UK
January 1996 through November 2013
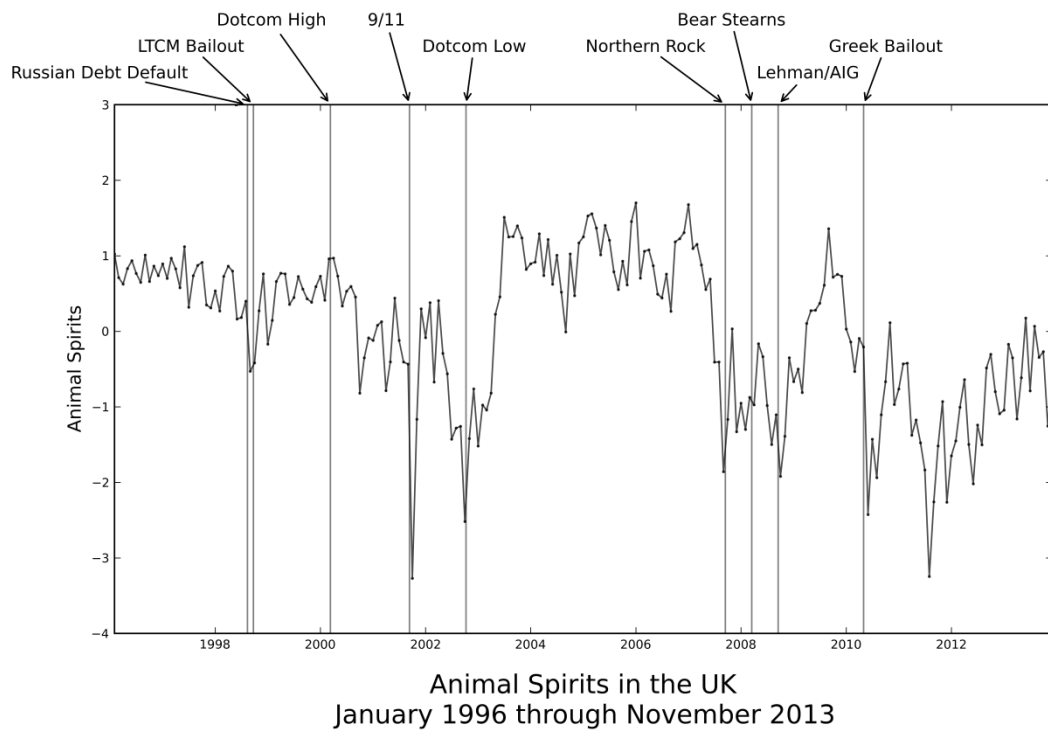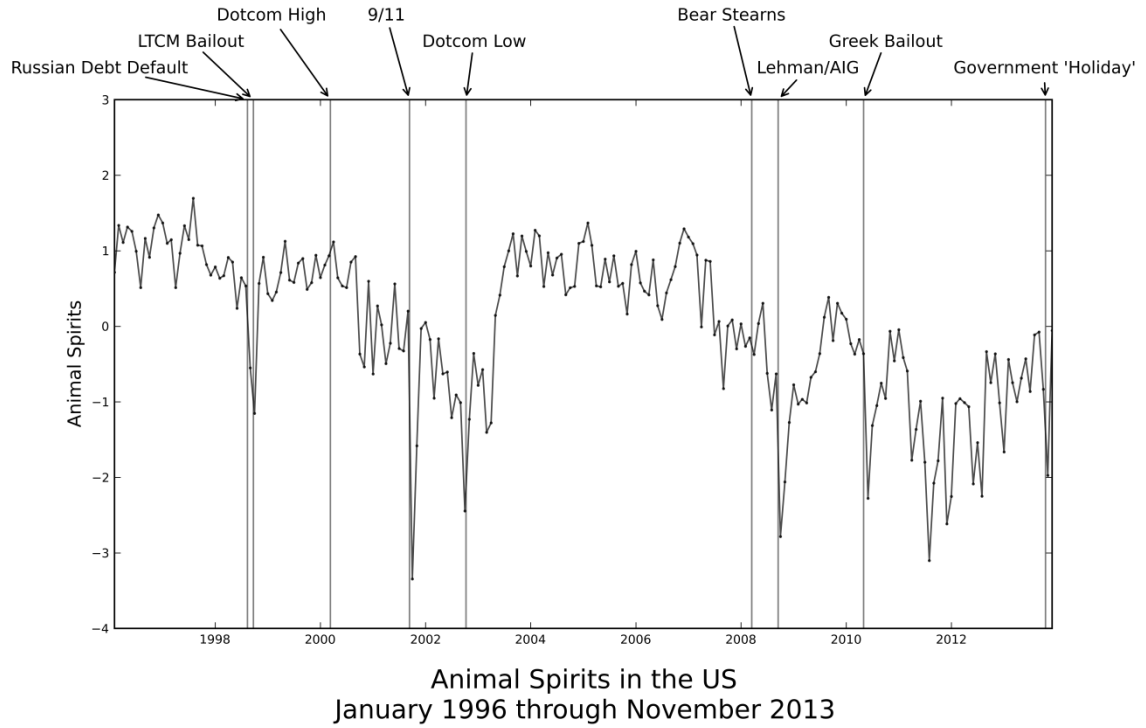
The two series share a number of similarities. This is not surprising, given that the correlation between the levels is 0.902 and between the monthly changes 0.757.

A number of major events are labelled. We discuss these briefly before considering some important but less immediately obvious aspects of the results. Six observations stand out.

1. The impact of the labelled events is very similar in both the US and the UK, with two exceptions. First, animal spirits dropped markedly in the US in October 2013, the month of the so-called government 'holiday', when there was deadlock in the political decision making process. Second, in September 2007, a small UK bank, Northern Rock, suffered the first bank run in Britain for some 150 years, leading to the bank being taken into public ownership shortly afterwards.

2. The animal spirits series in both the US and the UK appear to have given clear prior warning of the downturn, well in advance of any other indicators. In June 2007, the value fell sharply in both economies, to -0.113 in the US and -0.406 in the UK.   Compared to the mean values January 2004 through May 2007, these are, respectively, 2.55 and 3.49 standard deviations below. The fall was not just an erratic one-off event. By August 2007, the level in the US is 4.64 standard deviations below the January 2004- May 2007 mean, and in the UK it is 7.17 standard deviations below (using the standard deviation calculated January 2004- May 2007 in each case).

   This picture was not widely anticipated at the time. Although there had been rising concern about the economic situation, and at the very end of July 2007 the inter-bank market in London experienced a liquidity crisis, consensus economic forecasts remained reasonably buoyant. For example, the October 2008 edition of the *Bank of England Quarterly Bulletin* shows that as late as January 2008 the consensus forecasts for real GDP growth for 2009 were +2.7 per cent for the US

and +2.0 per cent for both the UK and the Eurozone. As late as August 2008, just one month before the collapse of Lehman Brothers, the consensus forecasts for 2009 still showed positive growth for 2009 in all three areas, albeit at levels close to zero.

The fall in our animal spirits series in 2007 pre-dates that of existing survey measures by several months. For example, the Michigan Consumer Confidence Index level in July 2007 was almost exactly the same as its mean value over the January 2004- May 2007 period. It did not fall below 2 standard deviations of this mean until November of that year, being 2.37 and 2.47 standard deviations below in November and December, and only 1.99 below in January 2008. The Federal Reserve Bank of St Louis' assessment of the probability of a recession in the US (Chauvet 1998, Chauvet and Piger 2008) has values less than 1 per cent up to and including September 2007. It rises to 2.4, 2.9 and 9.7 per cent in October, November and December respectively, and shows strong increases to 22.7, 39.3 and 53.8 per cent in January, February and March 2008. Furthermore, an index of economic uncertainty constructed using a number of proxy economic indicators by the Bank of England (Haddow et al. 2013), which matches closely the path of GDP growth, does not show any substantial increase in uncertainty until 2008.

3. The movements of the animal spirits series clearly reflect the impact of a number of key events. So, for example, there was a marked downturn in August and September 1998 at the time of both the Russian financial crisis and the bail-out of Long Term Capital Management. Interestingly, the average level of animal spirits in the first half of 1998, prior to the Russian and LTCM crises was distinctly lower than its average in 1996-97 in both countries. The 1996-97

average was 1.072 and 0.746 in the US and UK respectively, and in the first half of 1998 it was 0.657 and 0.499 respectively. In May 1998, the value fell to 0.238 in the US, 2.81 standard deviations below the 1996-97 average, and the level in the UK was 2.67 standard deviations below its 1996-97 average.

Animal spirits then recovered up to the time of the peak of the dotcom boom, March 2000 being when the NASDAQ peaked. The subsequent fall in animal spirits in both countries is a point to which we return in more detail below. The Bear Stearns crisis in 2007 appears to have had little impact. On the other hand, the impact of the Eurozone crisis in 2001 and, specifically, the Greek bailout confirms the argument of Dominguez and Shapiro (op cit.) that adverse events in the Eurozone had impacts on the US economy, In particular, they suggest that 'there are more to linkages than can be attributed to trade flows', a point which is demonstrated very clearly by the impact of the Greek bailout on animal spirits in America, Greece of course being a very small country relative to the size of the US.

4. The movement in the animal spirits indices since the depth of the recession in 2009 is particularly interesting. We now know, comparing 2009 with 2012, for example, that fixed investment plus inventory spending by firms rose by almost 30 per cent in America and by nearly 20 per cent in Britain[5] . In each case, this has been the main driver behind the economic recovery which has taken place. As we indicated above, like Keynes we attach importance not simply to the level of expectations to be derived from aviable information (the marginal efficiency of capital), but also to the degree of confidence with which any given view or

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[5] Bureau of Economic Analysis and Office for National Statistics estimates

level is held[6]. These observations are directly relevant to the two animal spirits

series. By the third quarter of 2009, GDP had started to rise again in the two

economies (indeed more generally thoughout the OECD). But the recovery has

been very weak by historical standards, perhaps more so than is generally

realised. Ormerod (2010) examines recessions in 17 Western countries since

1871[7]. Of the 191 examples, on 151 occasions real GDP had returned to its

previous peak level within one or two years.   On a further 15 occasions, the

peak level was regained after three years. Only 11 times out of the total sample

of 191 was it not regained after five years. In both economies, GDP peaked in the

winter of 2007/08. This level was not exceeded in the US until 2011Q2, over

three years later, and output in the UK is still to reach its previous peak level, five

years after the event.

The animal spirits series shed light from the perspective of Keynes' economic

theory on why the recovery has been so exceptionally weak. In the boom years,

from January 2004 through May 2007 (we return below to the choice of this

latter date), the mean and variance of the series in the US was 0.756 and 0.340,

and in the UK 0.968 and 0.393.   By the third quarter of 2009, real GDP had begun

to rise again in both economies. But from July 2009 through November 2013, the

mean level of animal spirits was far below that of the boom years, and the

standard deviation much higher. In the US the two figures are -0.906 and 0.814,

and in the UK the two are -0.806 and 0.894. So not only were animal spirits at

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[6] This position follows directly from his 1921 book Treatise on Probability, in which he takes issue with the frequentist approach in statistics. In the General Theory, he writes 'It would be foolish, in forming our expectation to attach great weight to matters which are very uncertain' (pp). He clarifies this latter phrase immediately 'By "very uncertain", I do not mean the same thing as "very improbable"' (pp).

[7] Much of the data is taken from the Maddison (1995) database

much lower levels, the degree of confidence with which agents held these beliefs was lower, as the sharp increase in variability indicates.

5. A further interesting period is that following the peak of the dotcom boom in March 2000. The pattern looks very similar to that after the fall from the peak values seen in May 2007 (the exceptional drop in September 2000 was the 9/11 event and there was a rapid bounce back, but to levels distinctly below those seen prior to March of that year). There was certainly a slow down in real economic activity during 2000 and throughout 2001, especially in the US. But we did not see the full-scale recession which began in the winter of 2007/08, after the falls in animal spirits which began in June 2007.

It does seem plausible that policy makers on both sides of the Atlantic managed to avert an economic recession in the early 2000s. The Federal Reserve cut interest rates eceptionally aggressively during 2001. At the start of the year, the federal funds rate stood at 6 per cent, and at the end of the year it was only 1.75 per cent. Interest rates also fell in the UK, the Bank of England cutting its rate from 6 to 4 per cent during 2001. But there was also a very marked shift in fiscal policy. Since 1994, the public sector deficit as a percentage of GDP had steadily fallen, and indeed by the early 2000s had turned into a surplus. This policy was reversed sharply, and a fiscal deficit was created. The movement in animal spirits during 2000, especially the second half of the year, looked ominous from the perspective of the real economy, but policy changes seem to have headed off a full scale recession.

We are not suggesting that the animal spirits series will always offer accurate, point predictions of the future course of GDP. The track record on forecasting GDP growth suggests that consistently accurate prediction is an exceptionally

difficult problem, with forecast errors of a comparable magnitude, albeit somewhat smaller, than the variability of the data itself. However, we do believe we have provided evidence to argue that we have created a potentially useful way to capture social-psychological dynamics within an economy. If so, the omission of such variables by simplifying assumptions that make little sense in the context of the reality of making decisions under uncertainty established in the wide scientific community is no longer necessary.

6. The animal spirits series in both the US and the UK adds explanatory power to an autoregressive model of the data for short-term prediction purposes. We obtain quarterly data for the animal spirits series by averaging the three monthly observations within each quarter. We use the latest estimates of quarter-on-quarter GDP growth, although of course over time these be subject to considerable revision. For the first quarter of 2008, for example, the initial estimate made in April 2008 was for an annualised growth rate of +0.6 per cent, which has subsequently been revised to one of -2.4 per cent.

The autocorrelation function of the US GDP data has significant values only at lags one and two, but in a regression only lag one is significant. Adding the level of the animal spirits series, we obtain, over the period 1996Q3 – 2013Q3:

$$\text{USGDPGROWTH}(t) = 0.0087 + 0.317 \cdot \text{USGDPGROWTH}(t-1) + 0.010 \cdot \text{AS}(t)$$

$$(0.002) \quad (0.110) \quad\quad\quad\quad\quad (0.003)$$

Residual standard error: 0.0056;   Adjusted R-squared 0.288

F-statistic: 14.77 on 2 and 66 degrees of freedom, p-value: 0.000

DW = 2.065; Ramsey F (3, 63) = 1.39; W = 0.48

(The figures in brackets are the estimated standard errors of the coefficients; DW is the Durbin-Watson statistic for first order autocorrelation; Ramsey is the Ramsey RESET specification test and W is the Shapiro-Wilk test for normality of the residuals)

The animal spirits series is available immediately at the end of any given quarter, whilst the initial estimate of GDP is not published until the next quarter. So the equation has predictive power.

A plot of the autocorrelation function of the residuals shows that it is flat, with no lags being outside the 95 per cent confidence interval around zero. The Durbin-Watson statistic confirms there is no first-order autocorrelation. The null hypothesis for the Ramsey RESET test is only rejected at a p-value of 0.254. However, the Shapiro-Wilk test is rejected at a p-value of 0.007, suggesting non-normality of the residuals, though this appears to be due entirely to the single observation in 2008Q4, when output fell at an annualised rate of 8.5 per cent. We confirmed the robustness of the equation by bootstrapping it 10,000 times in the statistical package R. The average values of the coefficients and the standard errors on the coefficients are very similar to those reported above.

The equation for the UK is very similar. The short-term autocorrelation in the GDP data is stronger than in the US, but it decays just as rapidly at higher lags.

UKGDPGROWTH(t) = 0.0044 + 0.646*UKGDPGROWTH(t-1) + 0.0068*AS(t)

(0.0013)   (0.086)   (0.0026)

Residual standard error: 0.0051;   Adjusted R-squared 0.530

F-statistic: 39.3 on 2 and 66 degrees of freedom, p-value: 0.000

DW = 1.813; Ramsey F (3,63) = 1.59; W = 0.951

 A plot of the autocorrelation function of the residuals shows that it is flat, with no lags being outside the 95 per cent confidence interval around zero. The Durbin-Watson statistic confirms there is no first-order autocorrelation. The null hypothesis for the Ramsey RESET test is only rejected at a p-value of 0.200. However, the Shapiro-Wilk test is rejected at a p-value of 0.010, suggesting non-normality of the residuals, though, as with the US, this appears to be due entirely to the single observation in 2008Q4, when output fell at an annualised rate of 8.5 per cent (by coincidence the same as in the US). We confirmed the robustness of the equation by bootstrapping it 10,000 times in the statistical package R. The average values of the coefficients and the standard errors on the coefficients were very similar to those reported above.

5. **Conclusion**

In this paper, we aimed to discover if, given that techniques now exist to take mental states and their influence on expectations into account, we could quantify the possible impact of social and psychological variables on shifts in the British and American economies. We argue this approach operationalizes Keynes' concept of animal spirits

Given ontological uncertainty, we argued agents may be more or less emotionally convinced that the information they have available provides the grounds to invest in opportunities which they hope may succeed but could also be loss-making.

To capture changes in the conviction agents have when making such decisions through time, we have derived indicators of shifts in the emotional content of narratives and

used them in conjunction with standard algorithmic text search methodologies, directed by our approach to emotion.

Analyzing an extensive database of Reuters news feeds, we have extracted shifts in "animal spirits" across time. Shifts in animal spirits (relative sentiment), measured in this way, turn down sharply in June 2007 in both the US and the UK economies, well in advance of forecast changes and standard survey measures of confidence.

Further, the animal spirits series account for the historically very weak recovery from the middle of 2009 to the present. Although the animal spirits series trends upwards, especially from 2011, the average is much lower in both the US and the UK than it was previously, and the standard deviation is much higher. Animal spirits have been not only low, but the degree of belief, of conviction to act, associated with any given level has been weak, as the high variability shows.

The animal spirits series do require interpretation. We are not suggesting that there is a time-invariant relationship between changes in the series and subsequent changes in real output over a one to two year time horizon. But we have shown that the series are informative at several key points over the 1996-2013 period. They have systematic explanatory power in very short term (one quarter ahead) projections of GDP growth.

We are certainly not suggesting in any way that the approach outlined constitutes the last word in creating ways to operationalise the concept of animal spirits. Rather, it illustrates the potential for obtaining different perspectives on the economy at the macro level in ways which have not previously been feasible. The purpose of this paper has bot been offer definitive explanations but to illustrate how the theoretical concept can be operationalised and time series of animal spirits constructed.

There were many reasons why macroeconomists chose not to follow Keynes ideas about animal spirits or have largely defined away the problems that arise if decisions must be made under ontological uncertainty. We believe that the method we have developed opens at least one way to begin to reverse this neglect. As it happens and depite our results, journalsts at Reuters News are instructed to write balanced emotionally neutral accounts. Reuters data is not rich in emotional content. Other data sources like broker reports may create more nuanced opportunities. Meanwhile, we believe we have shown it is possible to undertake rigorous analysis of mental states in the economy and that through exploring systematic shifts in mental states it will be possible to add to the understanding of economic change. It may also prove useful for detecting a wider range of responses to policy changes.

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<u>Appendix</u>

Prior to applying our measure of animal spirits, to be defined below, we extract the documents relevant to the target topics (US and UK). This is done by the use of 'regular expressions' – an algorithmic concept of matching logical patterns of characters with text.

Definition 1: Filtering
Let D be the set of all database 'objects' having key, value pairs (example keys are 'title', 'text', 'date', 'tags' etc.), '$\wedge$' be logical conjunction and '$\in$' be set-inclusion. Let T denote the collection of 'text' fields (e.g., article body texts) within the set of database objects D. Thus,

$$T = \{t[text]|(t \in D)\}.$$

Given T and a text pattern r we denote the subset of T consisting of those texts containing (matching) the pattern r by,

$$T[r \subseteq text] = \{t[text]|(t \in D) \wedge (r \subseteq t[text])\}.$$

We treat a piece of text as an ordered set of characters so that we may formally use the subset operator $\subseteq$. We extend the above notation by conditioning the texts on multiple properties.

Definition 2: Conditioning
For any collection C of potential values for a given property i (e.g. the 'date' property, the 'tags' property etc.) we define the conditional collection of texts $T[C]$ by

$$T[i \in C] = \{t[text]|(t \in D) \wedge (t[i] \in C)\}.$$

The extension to two collections C_1 and C_2 is straight forward:

$$T[i_1 \in C_1, i_2 \in C_2] = \{t[text]|(t \in D) \wedge (t[i_1] \in C_1) \wedge (t[i_2] \in C_2)\}.$$

These definitions allow us to formally state how we filter for English articles written by Reuters in the UK and the US. Finally, the set of non-sports and weather articles we consider UK focused can be written as,

$$T^{UK} = T[language = 'en', \; attribution = 'RTRS',' LONDON' \in text, \{SPO, ODD, WEA\} \cap tags = \emptyset],$$

and the US as,

$$T^{US} = T[language = 'en', \; attribution = 'RTRS',' NEW\ YORK|WASHINGTON' \in text, \{SPO, ODD, WEA\} \cap tags = \emptyset],$$

where '|' is the symbol of logical disjunction for a regular expression.

We can now define how we measure animal spirits within the two series above.

Definition 3: Animal Spirits

Given any topic of interest, we will define its information content within a collection of texts by the average number of times any token in the collection of tokens describing the topic appear in the texts. More specifically we use the following information metric:

$$I(d,T) = \frac{\sum_{t \in T} |\{w \in t \wedge w \in d\}|}{|T|} = \frac{\sum_{t \in T} \sum_{w \in t \wedge w \in d} 1}{|T|},$$

where T is a collection of texts t, each a list of tokens w, and d is a set of tokens representing the topic. Thus, our metric counts the number of topic tokens in the list of texts (e.g., articles) and scales that number by the total number of texts.

If we let a collection of anxiety words, A, and excitement words, E, describe the topic, d, in the above definition we arrive at the emotional statistics of interest, which we will denote $Anx(T) = I(A,T)$ and $Exc(T) = I(E,T)$.

For our measure of animal spirits we consider the difference of the two statistics. This turns out to be much more illustrative of the phenomena we measure and captures the contextual nature of emotion. We formally define this as

$$AS(T) := Exc(T) - Anx(T).$$

This allows us to create monthly time-series of animal spirits, for the UK and the US, by aggregating the UK and US collections by the date field,

$$\{AS[T^{UK}[date \in P]] | P \in \wp\}, \{AS[T^{US}[date \in P]] | P \in \wp\}$$

where $\wp$ denotes the set of distinct monthly time-periods (i.e. a set of sets of dates) covering the entire period from January 1996 through November 2013.