Big Data and Economic Forecasting: A Top-Down Approach Using Directed Algorithmic Text Analysis[1]

Rickard Nyman, Paul Ormerod[2], Robert Smith and David Tuckett

Centre for the Study of Decision-Making Uncertainty,

Faculty of Brain Sciences,

University College. London.

[1] The authors wish to acknowledge financial support to the Centre from the Institute of New Economic Thinking and assistance from the Bank of England. We are grateful to Aikaterini Fotopoulou of University College London for assistance in clarifying some questions of neurobiology.
[2] Corresponding author. pormerod@volterra.co.uk

1. Introduction

An important aim of economic forecasting is to make *ex ante* estimates of the likely values for output, inflation, employment, spending, etc., which are useful to guide action. Big Data provides many potentially exciting opportunities for discovering knowledge that might be relevant to this task in hitherto unconventional ways. However, it also raises important questions of theory and method. On the theoretical side, there are questions about what the value of data known today might be for what might be happening around now (nowcasting) or to what might happen months or years out (forecasting). On the method side, there is the need, to avoid drawing unreliable conclusions, to find ways to reduce the dimensionality of the information in Big Data in ways which enable it to be turned into meaningful knowledge.

The use of search engine data, for example, in an unstructured way can readily lead to spurious results. The Google Trend service provides data for millions of search queries and hundreds of search categories extending back to January 1, 2004. Given the processing power readily available, relationships which are apparently statistically significant can quite easily be discovered *ex post* between search terms and some potential dependent variable. But as Silver (2012), for example, points out, with so much data available and easy to process, many relationships may exist which seem significant on standard frequentist tests without there being any very satisfying explanation for them being in any way causal.

Results obtained through data mining in this way can only be interpreted *ex post*. Almost anything can be rationalised in this way. Without theoretical guidance, there is no way of knowing in advance even what the sign of any correlation ought to be. An example of data mining is a recent claim to have found a trading strategy, based upon the frequency with which the word 'debt' appeared on Google Trends, which would have delivered a 326 per cent return over the period 5 January 2004 until 22 February 2011 (Preis et al. 2013). However, a return only marginally lower could have been obtained, using the identical *ex post* strategy, based on the frequency with which the words 'colour' and 'restaurant' appeared

One alternative to mere data-mining is to examine big data such as Google Trends or Twitter using judgmentally selected variables which might reasonably be supposed to be of relevance to the particular problem. Bentley and Ormerod (2010), for example, use Google Trends data in the context of effective communication strategies regarding health issues. They fit a simple model to characterise the effective degree of social transmission versus decisions made individually in two rapidly-evolved issues, namely the world-wide interest in avian influenza, or 'bird flu', in 2005, and in H1N1, or 'swine flu', from late April to early May 2009.

Much more generally, Choi and Varian [2009a,b, 2011] describe how to use such methods and there is already a literature referring to such work (for example, Arola and Galan ,2012; McLaren and Shanbhoge, 2011; Hellerstein and Middeldorp, 2012; Suhoy, 2009; and Carrié-Swallow and Labbé, (2011). So, for instance, search engine queries in the "Vehicle Shopping" category could be good candidates for forecasting automobile sales, while queries such as "file for unemployment" could be useful in forecasting initial claims for unemployment benefits (Scott and Varian, 2012)

But the difficulty with using human judgment to select predictors is that the task does not easily scale to models where the number of possible predictors exceeds the number of observations – known as the "fat regression" problem. "Even if we restrict ourselves to using only categories of queries", as Scott and Varian (2012) point out, we will still have "several hundred possible predictors for 100 months of data".

Castle et al. [2009, 2010] describe and compare 21 techniques for variable selection for time-series forecasting. They fall into 4 major categories: Significance testing (forward and backward stepwise regression, Gets); Information criteria (AIC, BIC); Principle component and factor models (e.g. Stock and Watson [2010]) and Lasso, ridge regression and other penalized regression models (e.g., Hastie et al. [2009]). Scott and Varian themselves combine three Bayesian techniques: Kalman filtering, spike-and-slab regression, and model averaging. In their paper they illustrate such techniques to show how search engine query data may be selected less arbitrarily and more reliably as predictors in various contexts.

In this paper, we describe a new approach to economic forecasting, which is also based on the availability of “Big Data” and addresses the fundamental question of how to reduce the dimensionality of the information in ways which enable it to be turned into meaningful information. The econometric methodologies discussed immediately above offer one type of approach. Here, we offer a different one.

We describe a new methodological and statistical approach termed “Directed Algorithmic Text Analysis” (DATA), and illustrate how its use can improve considerably on consensus economic forecasts of the Michigan Consumer Index Survey, a key variable in understanding the state of the US economy.

The approach is based, like others, upon searching for particular terms in textual data bases. However, in contrast to the econometric approaches, our methodology is based upon a theory of human decision making under radical uncertainty. The search is *directed* by the theory. This direction dramatically reduces the dimensionality of the search. We look for words which convey a very limited number of emotions, two to be precise. As in other approaches, we also use regression analysis, but the choice of variables comes from the underlying theory of decision making.

In section 2, we introduce conviction narrative theory, a social-psychological theory of agent behaviour, which provides a framework as to how to define and measure sentiment relevant to forecasting macroeconomic events. In section 3 we set out the directed algorithmic text analysis (DATA) methodology we have developed to extract relative sentiment shifts in conviction narratives over time from textual data bases. We also describe the application of the technique to the prediction of the Michigan Consumer Survey Index. We present results in section 4, using as a benchmark the consensus forecasts made by economists and reported by Reuters. We offer a brief discussion and conclusion in section 5.

2. Conviction Narrative Theory

The concept of conviction narratives (Chong and Tuckett, 2014) is based on a social-psychological theory of action under uncertainty. It builds on the view of emotion as a human resource (Stets and Osborn, 2008; Bandelj, 2009; Berezin, 2009; Stets, 2010) - for instance, to anticipate good or bad outcomes under uncertainty (Kemper, 2006) - and narrative as a largely successful way of apprehending complex situations - so that the imagined future course for events has a sense of truth (Bruner, 1986, 1990, 1991; Mar and Oatley, 2008).

Embedded in local social contexts, conviction narratives enable agents to overcome the ambivalence that is created by entering into any dependent relationship where one can lose or gain as time unfolds (Smelser, 1998; Pixley, 2009; Tuckett and Taffler; 2008). Ambivalent relationships necessarily create emotional conflict - between hope and fear or excitement and doubt. Any economic agent required to act to begin such a relationship faces the fact that their actions make them dependent on uncertain outcomes. The decision necessarily generates both *anxiety* about possible future loss and *excitement* about possible future profit. It is these two emotions, anxiety and excitement, which play a central role in conviction narratives.

We can conceive of a conviction narrative as an internal representation of each economic agent's environment that creates enough excitement relative to the level of anxiety to allow the agent to feel committed to actions that might generate loss. We can then think of the collection of conviction narratives existing within the economy and/or its different sectors as expressing the current state of narrative confidence about the future. The measure we will shortly introduce seeks to assess such shifting economic confidence about the future by assessing shifts in the relative quantities of excitement and anxiety in relevant texts thus allowing a time series to be constructed to track the shifts.

Conviction narrative theory draws on modern neurobiological theories in which cognition is associated with the functions of observable brain networks and allied neurobiological processes (Kasam et al, 2013). It is now well-established that several aspects of cognition are predictive and anticipatory in the sense that the brain mainly represents events by predicting the states of the organism in the world and in so doing stimulates reactions such as approach or flight that fulfill its predictions (Friston, 2010). In this view of mental functioning, feelings, emotions and cognitions are not necessary mental events in opposition but different facets of the predictive nature of brain functioning that can support each other, ultimately allowing agents to commit to decisions rapidly and effectively (Damasio, 1994). This is particularly the case where there is uncertainty, and outcomes may not be confidently knowable for some time to come.

Conviction narrative theory (Chong and Tuckett, 2014; Tuckett, Smith and Nyman, 2014) provides the opportunity to go beyond simplisitic "positive/negative", "optimistic/pessimistic", characterizations of economic sentiment, which are essentially atheoretical, to specify precisely the kinds and levels of human affect likely to be found in narrative texts when decisions are taken to act.

3. Directed Algorithmic Text Analysis (DATA): An Empirical Application

Machine learning algorithms offer the potential to carry out rigorous and extensive analysis of textual material in order to derive knowledge (Hofmann, 2001; Ikonomakis, Kotsiantis & Tampakas, 2005; Pang, Lee & Vaithyanathan, 2002; Pang & Lee, 2005; Sebastiani, 2002; Turney, 2002). Our approach has been to develop algorithms to analyse text archives (such as the daily Reuters news feeds, company emails, internal memoranda or for this paper, broker reports held on file at the Bank of England) to extract time series of relative sentiment shifts that might forecast aspects of the economy.

A formal exposition of the methodology can be found in the appendix. Essentially, our approach is to select variables, directed by the relevant theory of decision making, for use as explanatory factors in a regression without making any distributional assumptions. We can explore large text data sets, using a causal hypothesis about what drives agents' confidence in the economy, namely the theory of conviction narratives.

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).

We construct relative sentiment shift indicators directly and transparently using our DATA methodology. We then assess the statistical significance of the correlations that emerge rigorously, using a framework which is designed to replicate a strict *ex ante* test.

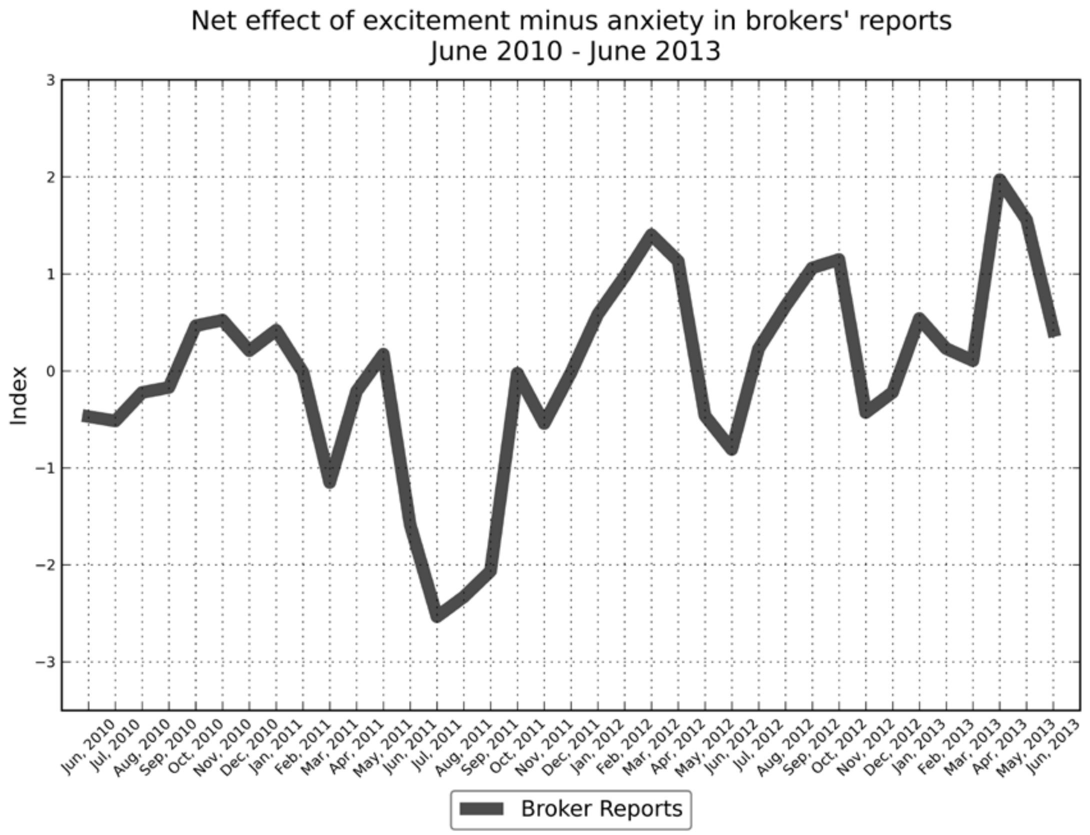
In this example we analyse an archive of 14 brokers from June 2010 through June 2013 consisting of documents of a primarily global economic focus. The archive consists of approximately 111 documents per month. The documents are very long (up to 50 pages in some cases), and so we pick up on a large number of words. In total we arrive at 37 monthly data points. 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 relative sentiment shifts in the content of narratives within the collection, is to compute the difference between the attractor (exciting) and repellor (anxiety) emotion scores. For the formal definitions we refer to the appendix.

We construct from this a single measure of relative sentiment (BROKER) which we use for analytical purposes, defined as the difference between the frequency of excitement words and the frequency of anxiety words in any given month, normalized by dividing by the total number of characters[3] in the data base. Figure 1 plots relative sentiment shifts over the period June 2010 through June 2013.

Figure 1

[3] In general, the total number of words or documents is the divisor, but in this particular instance some of the documents contain tables and others do not, so that the total number of characters is more appropriate



In a companion paper we have shown that the shifts in a time series derived in this way from the much more general Reuters News Archive 1996-2013) can both represent and sometimes predict shifts in GDP and major economic events (Tuckett et al, 2014). Here we turn to the question of formal “ex ante” forecasting the MCI with broker data.

4. Forecasting the Michigan Confidence Index

The MCI was created as a means to assess consumers’ ability and willingness to buy[4]. There are sub-indices, but this is the main one. The survey is carried

[4] [4] Such measurements were first created in the United States at a time when policy makers were interested in influencing mass demand as a part of Keynesian macroeconomic steering efforts. They derived from the work of the Hungarian-born émigré George Katona who was the driving force in developing the first consumer confidence index from the University of Michigan Economic Behaviour Program, which conducted the Survey of Consumer Finances for the Federal Reserve between 1946 and 1971 as well as the still-ongoing Survey of Consumer Attitudes, which is used by the Department of Commerce. These surveys asked representative samples of households about their views and expectations with regard to their own finances and to the state of business and the economy as a whole. Building on their survey data, Katona’s team calculated an index which - like a barometer - aimed to predict consumer behaviour in the near future. Published since 1952, the Index of Consumer Sentiment is included in the Department of Commerce’s Composite Index of Leading Indicators. The conceptual basis of consumer confidence measurements was heavily influenced by Katona’s interest in combining economic and psychological research. Similar measures are now constructed worldwide.

out with at least 500 phone interviews, during a period of around 2 weeks, in which approximately 50 questions are asked.

Survey results are released twice each month at 10.00 a.m. Eastern Time: preliminary estimates are published usually (variations occur during the winter season) on the second Friday of each month, and final results on the fourth Friday.

There is a very high correlation of 0.966 between the preliminary and final index. The correlation between the change in the preliminary index in any given month from the final in the previous month, and change in the final itself remains high, at 0.905. The challenge is therefore not so much to forecast the change in the final estimate of the index at time t+1 from the final estimate at time t. Rather, it is to predict the change in the preliminary index at time t+1 from the final estimate at time t. We refer to this latter variable as DIFFPRELIM.

As a benchmark against which to judge predictions made by Directed Algorithmic Text Analysis, based an analysis on conviction narratives, we use the consensus forecasts of DIFFPRELIM made by economists and reported by Reuters. We consider the period May 2012 through July 2013. Over this period, the consensus predictions of DIFFPRELIM were poor. Even the sign of the variable was only predicted correctly on 7 out of the 15 months.

A linear regression of DIFFPRELIM on the change in the preliminary on the previous final predicted by the consensus forecast (which we describe as DIFFCONSENSUS)[5].confirms the poor record.

Over the period May 2012 through July 2013,

(1) $$DIFFPRELIM = -1.293 + 1.972*DIFFCONSENSUS$$

(1.084) (1.178)

Residual standard error: 4.045 Adjusted R-squared 0.114

F-statistic: 2.804 on 1 and 13 degrees of freedom, p-value: 0.118

The figures in brackets are the estimated standard errors of the coefficients.

The explanatory power of the equation is very low. In fact, it is essentially

[5] The autocorrelation function of each variable contains no lags which are significantly different from zero, so the two variables have the same order of integration

not significantly different from zero. In other words, the consensus forecasts have very little value in terms of predicting the change in the preliminary index from the level of the final index in the previous month.

Next, we compare predictions made by the consensus of economists for DIFFPRELIM with the predictions generated by a simple regression of DIFFPRELIM at time t on DIFFBROKER at time t-1, where DIFFBROKER is the change in BROKER on the previous month.

The time stamp of the data is important to explain. It is crucial to understanding the significance of the results.

Initially, we estimate the regression using the data on DIFFPRELIM from August 2010 through April 2012. The first observation in this sample is the value of the preliminary index in August 2010 minus the value of the final observation in July 2010. The corresponding data point for the series BROKER is the change in the value of BROKER between July and June 2010. In other words, we regress DIFFPRELIM on information which would have been available at the end of the *previous* month to which DIFFPRELIM relates.

Using data on DIFFPRELIM from August 2010 through April 2012 and data on DIFFBROKER from July 2010 through March 2012, we obtain[6]:

*(2) DIFFPRELIM = -0.877 + 0.681*DIFFBROKER*

(0.766) (0.261)

Residual standard error: 3.486 Adjusted R-squared 0.225

F-statistic: 6.815 on 1 and 19 degrees of freedom, p-value: 0.017

DW = 1.92; Ramsey F (3,30) = 0.69; W = 0.96

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 equation is well-specified.

[6] Again, the autocorrelation function of each variable contains no lags which are significantly different from zero, so the two variables have the same order of integration

To generate forecasts of the preliminary estimates of the Michigan index for May 2012, we use the coefficients in equation (2) above, and the data for DIFFBROKER in April 2012. In other words, to predict the May value of the index, we use information which was available at the end of April.

We then repeat the analysis, moving the sample forward one month at a time, until we predict the index in July 2013 using the equation estimated with DIFFPRELIM from August 2010 through June 2013 and DIFFBROKER July 2010 through May 2013. The prediction for July 2013 uses the value of DIFFBROKER in June 2013. Again, to emphasise, when making the prediction we only use information which was available at the previous month. This replicates as far as possible an *ex ante* forecasting situation.

We also want to emphasise that the text analysis was only carried out once. In other words, we applied our general methodology of DATA to this particular text data base and used the results to make predictions, as described above. We did not do repeated searches of the data base, using for example only sub-sets of the complete set of words which represent excitement and anxiety, or giving words different weights in order to improve the forecast performance. *Ex post,* it would almost certainly be possible to achieve an apparent improvement in 'forecast' performance by carrying out such procedures, but as a way of replicating an *ex ante* forecasting situation, it would be wholly invalid.

Further, we specified the very simple functional form in equation (2) and then carried out the regressions. We did not modify this in any way in order for the equations to perform better on statistical tests of validation. The test statistics reported with the equations therefore satisfy completely the requirements of statistical theory and their power can be relied upon. We make this point because many regressions, especially on time series data, reported in the academic econometric literature, appear to satisfy an impressive battery of specification tests. But usually this is only achieved by modifying the specification of the equation, either in terms of explanatory variables or in terms of functional form, in order that the equation does in fact satisfy such tests. But in these circumstances, the true power of the tests is in general unknown, except that it is less than that suggested by statistical theory.

To recap, the consensus forecasts made by economists over the period May 2012 through July 2013 only get the sign of the change correct on 7 out of 15 equations, and a regression of the actual value of DIFFPRELIM on the changes implied by the consensus forecasts has effectively zero statistical power. This is the benchmark against which we judge our predictions.

Our methodology captures the correct value of the sign of DIFFPRELIM on 12 out of 15 occasions.

The regression comparable to (1) using the BROKER data has an adjusted R squared of 0.486 compared to the 0.114 of the consensus predictions of DIFFPRELIM. It has genuine power and the predictions are very much better than that achieved from consensus economic forecasts. The predictions are unbiased, given that the intercept is not significantly different from zero and the coefficient on the explanatory variable is not significantly different from one.

The difference in the forecasting performance of the consensus economic forecasts (CONSENSUS) and BROKER is seen very clearly comparing Figures 2 and 3. Figure 2 plots the difference between the preliminary estimate and the final value in the previous month and the prediction given by the consensus. Figure 3 plots the difference between Broker and the preliminary estimate.

Figure 2

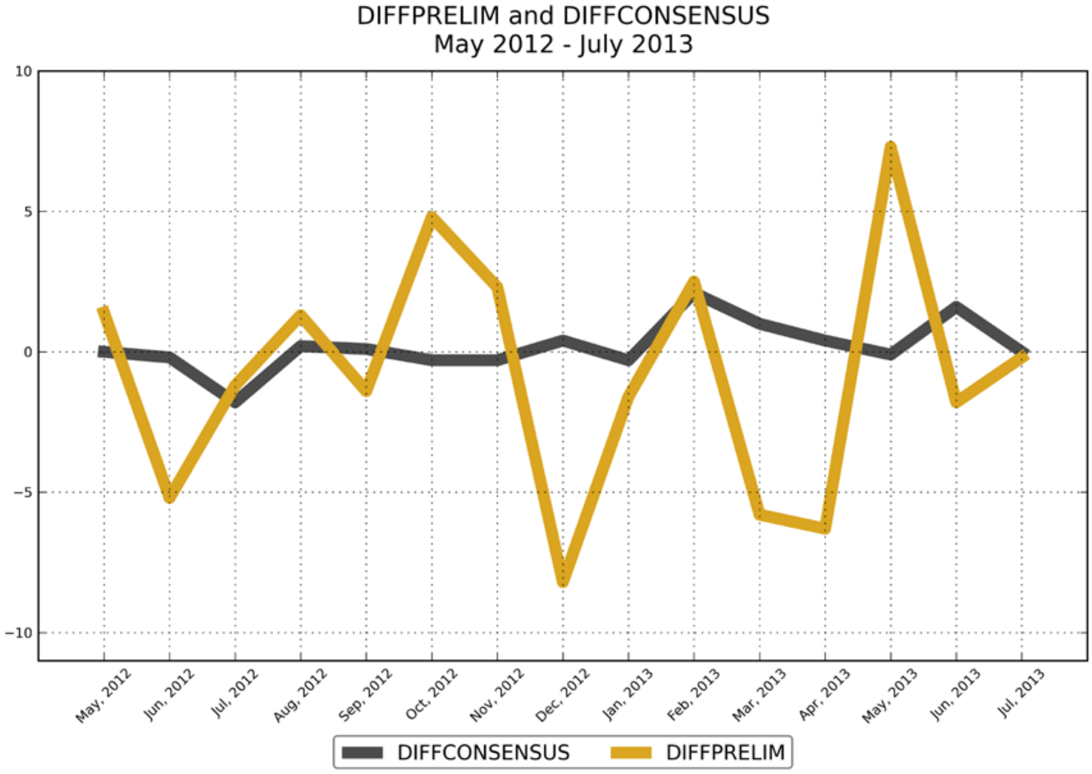
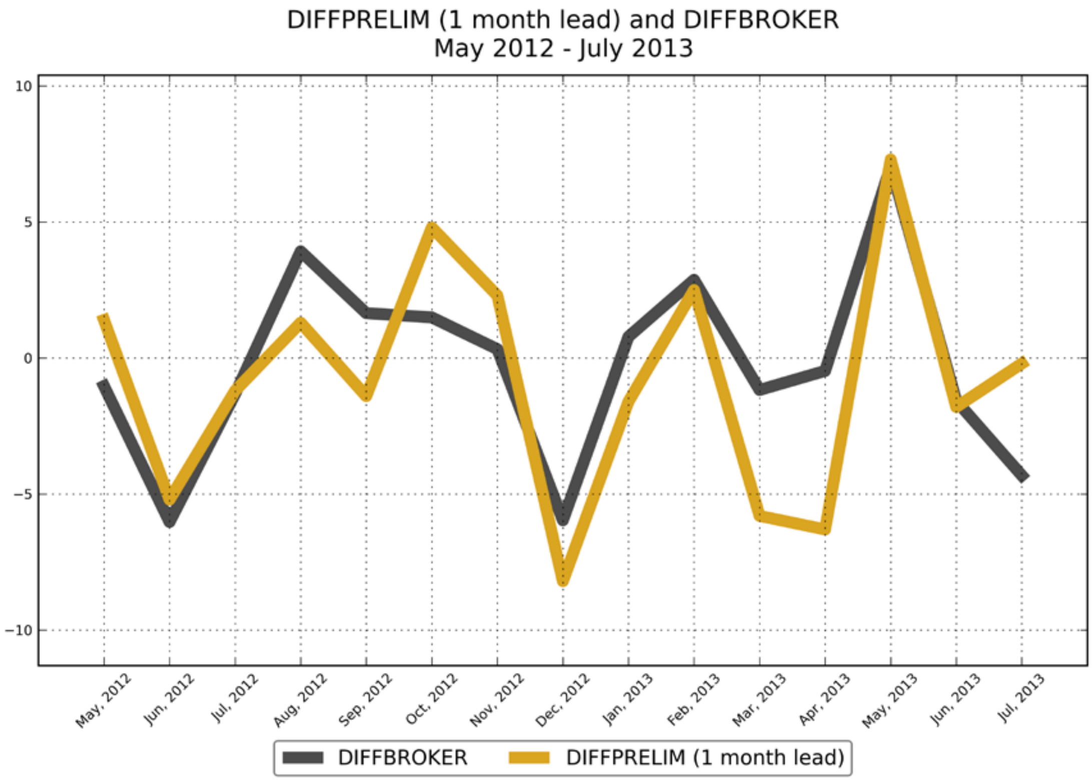

DIFFPRELIM and DIFFCONSENSUS
May 2012 - July 2013
10
5
0
−5
−10
May, 2012
Jun, 2012
Jul, 2012
Aug, 2012
Sep, 2012
Oct, 2012
Nov, 2012
Dec, 2012
Jan, 2013
Feb, 2013
Mar, 2013
Apr, 2013
May, 2013
Jun, 2013
Jul, 2013
DIFFCONSENSUS
DIFFPRELIM

Figure 3


DIFFPRELIM (1 month lead) and DIFFBROKER
May 2012 - July 2013
10
5
0
−5
−10
May, 2012
Jun, 2012
Jul, 2012
Aug, 2012
Sep, 2012
Oct, 2012
Nov, 2012
Dec, 2012
Jan, 2013
Feb, 2013
Mar, 2013
Apr, 2013
May, 2013
Jun, 2013
Jul, 2013
DIFFBROKER
DIFFPRELIM (1 month lead)

The results described above are forecasts rather than 'nowcasts'. In other words, they are forecasts about the value of a variable in the future rather than an estimate at time to of the value of a variable at the same time. However, the preliminary estimate of the MCI appears in the first half of the month, and we use information up to and including the last day of the previous month. So the prediction is very short-term (even though it could be used in trading strategies).

We therefore examined the ability of the BROKER series to predict the preliminary value of the MCI further ahead than the immediate next month. We consider 2, 3 and 4 months ahead. So, using information available at the end of April 2012, for example, the prediction 2 months ahead is for the change in the preliminary value of the MCI in June 2012 on the final value in April 2012. Similarly, the 3 months ahead is the change in the preliminary value of the MCI in July 2012 on the final value in April 2012, and the 4 month ahead is the change in the preliminary value of the MCI in August 2012 on the final value in April 2012.

The resulting predictions are plotted in Figures 4(a) to (c). Even 4 months ahead, there is some predictive power in the BROKER data, although the performance deteriorates the further ahead the prediction is made, as one would expect. In terms of the correct prediction of the sign of the change in the preliminary index, defined as in the paragraph immediately above, for the 2 month ahead it is 11/15, for the 3 month 8/15 and for the 4 month 7/15.

Figure 4 a)

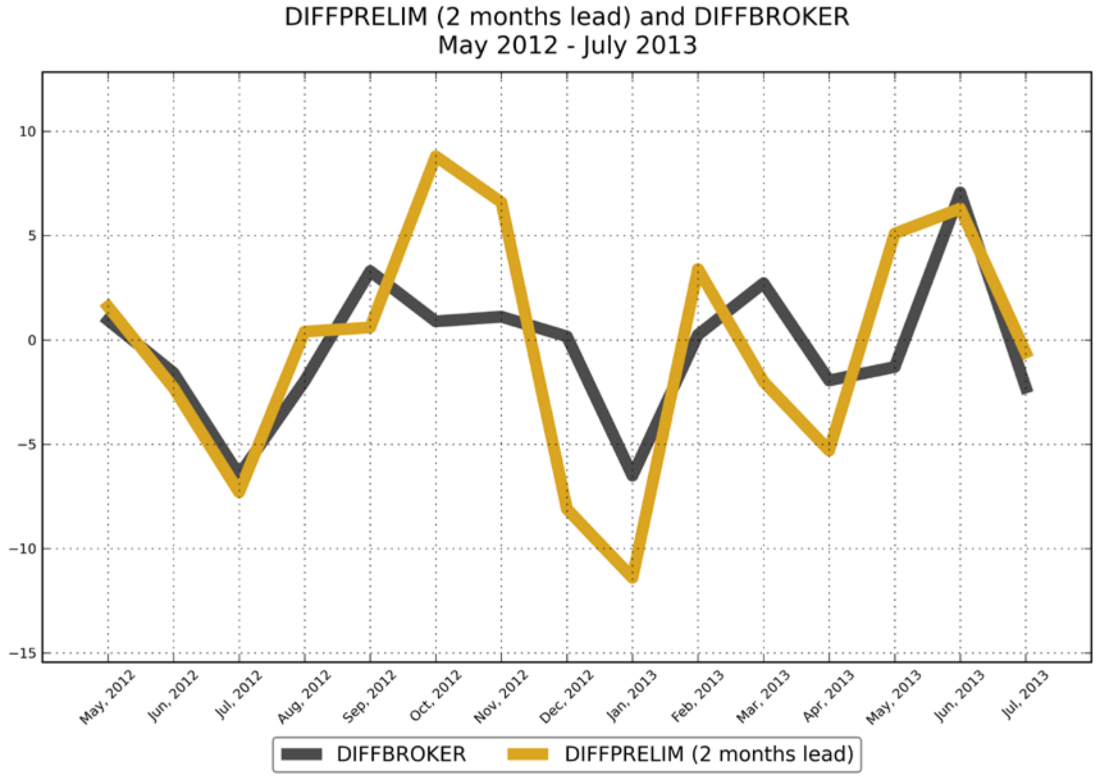


Figure 4 b)

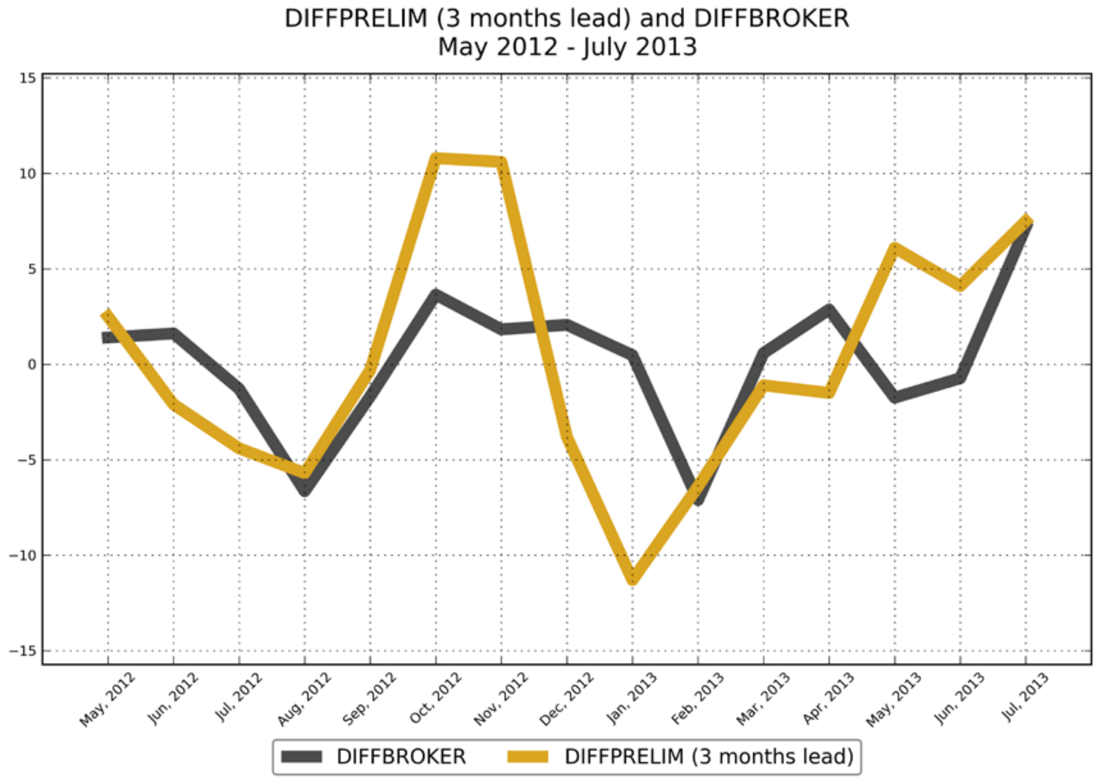
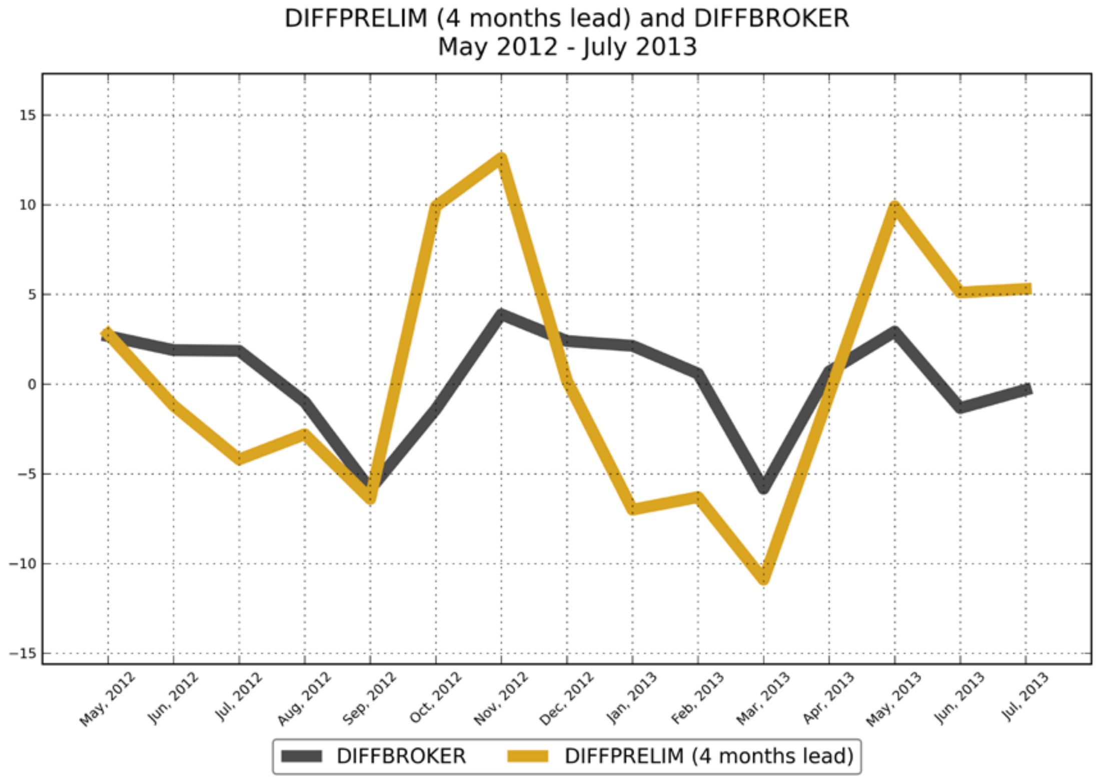


Figure 4 c)



5. Discussion and Conclusion

The Michigan Consumer Sentiment Index is important not only in its own right as an indicator of the current state of consumer confidence in America, but it is also the focus of many trades on financial markets. Economists make predictions of this index, month by month, and their views are polled by Reuters and the consensus is published. The final value of the index for any given month is published essentially at the end of the month, but a preliminary estimate is also published in the first half of the month. This preliminary estimate is very strongly correlated with the final value, and is available to the economists when they make their predictions.

The real challenge, is therefore, to predict not the final, but the preliminary value of the index. More specifically, the challenge is to predict the change in the preliminary estimate from the final value of the previous month. The performance of the economic consensus forecasts of this change over the 15 months from May 2012 through July 2013 is poor. Even the sign of the change is correctly predicted on only 7 out of the 15 occasions, no better than a random guess. A regression of the actual change on the predictive change has essentially no predictive power.

The approach we have presented, grounded in the social-psychological theory of conviction narratives and using directed algorithmic text analysis with a database of brokers' reports generates a time series which indicates the net level of excitement minus anxiety found in the reports.

We replicate as far as possible a genuine ex ante forecasting situation over the same 15 months from May 2012 through July 2013. These predictions give the correct sign on 12 out of the 15 occasions, and have significant explanatory power. The methodology can readily be applied to other text databases in the same or other forecasting contexts. It can undoubtedly be refined. For example, all documents are given equal weight in our analysis, even though in practice some may be more influential than others.

Technical Appendix.

Relative Sentiment Shift Measurement

Prior to applying our measure of relative sentiment shifts, to be defined below, we extract the documents relevant to the target topic. This is done by the use of 'regular expressions' – an algorithmic concept of matching logical patterns of characters with text. In this particular case no filtering has been applied - we have made use of the entire archive of broker reports available to us.

Definition 1: Filtering

Let D be the set of all database 'objects' having key, value pairs (example keys are 'title', 'text', 'date', 'tags' etc.), '

References

Arola, Concha and Galan, Enrique (2012) Tracking the future on the web: Construction of leading indicators using internet searches. Technical report, Bank of Spain. URL http://www.bde.es/webbde/SES/Secciones/Publicaciones/ Publicaciones Seriadas/Documentos Ocasionales/12/Fich/do1203e.pdf.

Bandelj, N (2009) Emotions in economic action and interaction. Theor. Soc. 38:

Bentley, R. Alexander & Ormerod, Paul, 2010. "A rapid method for assessing social versus independent interest in health issues: A case study of 'bird flu' and 'swine flu'," Social Science & Medicine, Elsevier, vol. 71(3), pages 482-485, August.

Berezin, M. ________(2009) Exploring emotions and the economy: new conributions from sociological theory. Theor. Soc. 38:335-346.

Bruner, Jerome. (1986) Actual Minds, Possible Worlds. Harvard University Press.

__________ (1990) Acts of Meaning. Harvard University Press.

__________(1991) The Narrative Construction of Reality. Critical Inquiry, 18, 1, 1-21.

Carriere-Swallow, Yan and Labbé, Felipe.(2011) Nowcasting with google trends in an emerging market. *Journal of Forecasting*. doi: 10.1002/for.1252. URL http://ideas.repec. org/p/chb/bcchwp/588.html. Working Papers Central Bank of Chile 588.

Castle, Jennifer L, Qin, Xiaochuan and Reed, W. Robert. How to pick the best regression equation: A review and comparison of model selection algorithms. Technical Report 13/2009, Department of Economics, University of Canterbury, 2009. URL http://www. econ.canterbury.ac.nz/RePEc/cbt/econwp/0913.pdf.

Castle, Jennifer L. and Fawcett, Nicholas W. P. and Hendry, David F. (2010). Evaluating automatic model selection. Technical Report 474, Department of Economics, University of Oxford, 2010. URL http://economics.ouls.ox.ac.uk/14734/1/paper474.pdf.

Choi, Hyunyoung and Varian, Hal. (2009a) Predicting the present with Google Trends. Tech- nical report, Google, 2009a. URL http://google.com/googleblogs/pdfs/google_ predicting_the_present.pdf.

Choi, Hyunyoung and Varian, Hal. (2009b) Predicting initial claims for unemployment insurance using Google Trends. Technical report, Google. URL http://research.google.com/ archive/papers/initialclaimsUS.pdf.

Choi, Hyunyoung and Varian, Hal. (2011). Using search engine data for nowcasting— an illustration.

Kemper, T. D. (2006). Power and status and the power-status theory of emotions. In J. E. Stets & J. H. Turner (Eds.), Handbook of the sociology of emotions (pp. 87–113). New York: Springer.

Mar, R. A. & Oatley, K. (2008) The function of fiction is the abstraction and simulation of social experience. Perspectives on Psychological Science 3(3):173–92

McLaren, Nick and Shanbhoge, Rachana. (2011) Using internet search data as economic indicators. Bank of England Quarterly Bulletin, June 2011. URL http://www.bankofengland.co. uk/publications/quarterlybulletin/qb110206.pdf.

Pixley, J. (2009) Exploring emotions and the economy: new conributions from sociological theory. Theor. Soc. 38:335-346.

Pang, B., Lee, L., 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In: Proceedings of the ACL, 115-124.

Preis, T., Moat, H.S. & Stanley, H.E. (2013). Quantifying Trading Behavior in Financial Markets Using Google Trends. Scientific Reports, DOI: 10.1038/srep01684

Scott, Steven L. and Varian, Hal R. (2012). Bayesian Variable Selection for Nowcasting Economic Time Series. December 31 Draft at

Sebastiani, F. (2002). Machine learning in automated text categorization. ACM Computing Surveys (CSUR) Surveys. Volume 34 Issue 1, 1-47

Silver, N. (2012). The Signal and the Noise: Why Most Predictions Fail – but Some Don't. Penguin Press.

Smelser, N. (1998). 'The Rational and the Ambivalent in the Social Sciences'. American Sociological Review, 63, 1–16.

Stets, J. E., (2010) Future Directions in the Sociology of Emotions. 2: 265–268

Stets, J. E., & Osborn, S. N. (2008). Injustice and emotions using identity theory. Advances in Group Processes, 25, 257–285.

Stock, James and Watson, Mark. (2010) Dynamic factor models. In M. Clements and D. Hendry, editors, Oxford Handbook of Economic Forecasting. Oxford

University Press, 2010. URL
http://www.economics.harvard.edu/faculty/stock/files/DynamicFactorModels.pdf

Strauss, Viktor, M. (2013) Emotional Values of Words in Finance: Anxiety about Losses and Excitement about Gains. M.Sc. thesis in Social Cognition, University College London.

Suhoy, Tanya. (2009) Query indices and a 2008 downturn: Israeli data.
Technical report, Bank of Israel, 2009. URL
http://www.bankisrael.gov.il/deptdata/mehkar/papers/dp0906e. pdf.

Tuckett, David, and Taffler, R. J., (2008). Phantastic Objects and the Financial Market's Sense of Reality: A Psychoanalytic Contribution to the Understanding of Stock Market Instability. International Journal of Psychoanalysis, 89, 2, pp 389-412.

Tuckett, D., Smith, R. E. & Nyman, R. (2013). Tracking Phantastic Objects: A Computer Algorithmic Investigation of Narrative Evolution in Unstructured Data Sources. Under review.

Tuckett, D., Ormerod, P., Smith, R.E., & Nyman, R. (2013). Bringing Social-Psychological Variables into Economic Modelling: Uncertainty, Animal Spirits and the Recovery from the Great Recession.

Turney, P.D. (2002). Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews. In: ACL '02 Proceedings of the 40th Annual Meeting on Association for Computational Linguistics,. 417-424.